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Agile data-oriented research tools to support smallholder farm system transformation

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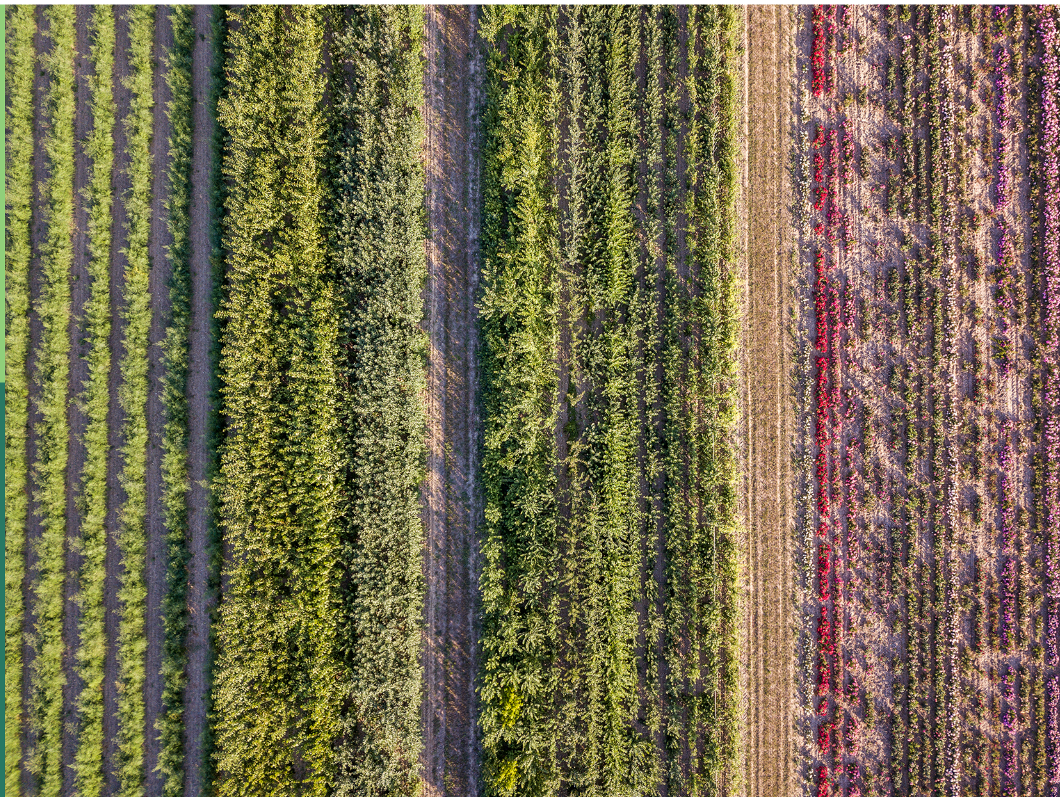

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Agile data-oriented research tools to support smallholder farm system transformation

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Editorial: Agile data-oriented research tools to support smallholder farm system transformation

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Editorial on the Research Topic
Agile data-oriented research tools to support smallholder farm system transformation

1. Introduction

Smallholder farming systems produce the majority of the food consumed in many lower- and middle-income countries, and contribute significantly to national and local economies. However, a transformation is needed to deliver food security and decent incomes for the farmers themselves, and to feed the growing populations within those countries. This transformation must be environmentally and socially sustainable to be successful in the long term. One obstacle is the lack of good quality, timely, and targeted information.

In this editorial we unpack three key terms from the title of this Research Topic, and use the articles published to illustrate those terms. The key terms are "data-oriented," "agile," and "system transformation." The term "data-oriented" is used to refer to big data, the compilation of data, replicable analysis methods, and the various other developments facilitated by the digital revolution. Dealing with one of the negative features of the digital revolution is a recurring theme: information overload—or "infobesity"—whereby the flood of non-useful information hampers rational decision making. The term "agile" is used to refer to an emerging but not yet clearly defined methodological style, which tends to be enabled by the digital revolution, attempts to deal with problems of infobesity, and attempts to deal with the challenge of conducting outcome-oriented science in complex and uncertain situations. The term "system transformation" refers to efforts to stimulate and facilitate sustainability transitions within the smallholder farming sector. These terms are explored further below. The Research Topic focuses on research tools (tools or methods for knowledge creation) and excludes tools which are primarily geared toward the implementation of farming activities.

2. Data orientation

Digital and data technologies have far-reaching implications in many sectors, including agriculture (Klerkx et al., 2019). Much of the innovation has been in industrialized farming systems using technology to increase the efficiency of production (Wolfert et al., 2017; Basso and Antle, 2020). In less industrialized farming systems, digital agriculture has been related more to information services, for example extension advice, weather, or marketing information (Malabo Montpellier Panel, 2019). The potential for digital and data technologies to alter agricultural innovation (for better or worse) has been recognized but not received much attention (Fielke et al., 2020). One of the major side-effects of the digital revolution has been massively increased data collection, and practically unlimited data storage. This opens up positive but also negative possibilities—the temptation to record too much non-useful information can lead to infobesity.

The articles within this Research Topic seek to address infobesity in two main ways. The first is to make better use of the extant huge data resources, through improved data management, replicable analyses, and other best practices. The second way is to control our scientific appetite for data, *via* the creation of agile tools and methods, and the re-orientation of researchers' attitudes.

Gorman et al. conducted a systematic review of recent studies using household-level smallholder survey data and found that in the vast majority of cases best practices were not being followed. Only 14% of the studies made their data accessible. After descriptive statistics, linear regression was the most widely used analysis method (64% of studies); and was generally used inappropriately, to explain context specific and complex associations without adequate reference to that context or complexity. More than half (59%) drew conclusions which extended beyond the scope of their data or analysis. This rather damning analysis points to a lack of coordination which prevents the research community working on smallholder development from building up a coherent body of evidence over time. We should learn from the field of medicine in which standards have been agreed on what data is collected, how impact is evaluated, and how metadata and study context are recorded (von Elm et al., 2007; Field et al., 2014).

Kruseman puts forward a metadata schema to overcome the lack of interoperability in messy socio-economic datasets, borrowing concepts from information science and the development of the World Wide Web. Devare et al. describe a tool for creating digital agronomic field books, in which data is recorded and published according to best practices, including linkages to agronomic ontologies and publication in open access databases. Andrade et al. go further along the data pipeline, beyond data acquisition and organization to deliver analysis and actionable insights to decision makers within agricultural value chains. They note a widening gap between those who can and cannot process the modern forms of data, for whom analysis is a key bottleneck.

3. Agile tools and use of agile data

The agile methods in this Research Topic were enabled by the digital revolution, and have developed in response to the problems of infobesity. But that is only half of the story. Agile methods are also necessitated by a fundamental challenge faced when applying the scientific method in pursuit of agricultural sustainable development in lower- and middle-income countries. There is a tension between the scientific desire to collect comprehensive, granular, and precise information vs. the practical realities of conducting that research in resource-constrained environments where there is typically poor record keeping, a low level of education, and low institutional capacity. Attempts to record overly-precise or overly-granular information can be counter-productive, undermining data quality, relationships, and taking resources away from other important scientific activities, such as interpretation, publishing, and stakeholder engagement. The application of science in agricultural development fits many of the features of post-normal science (Funtowicz and Ravetz, 1993), whereby facts tend to change depending on the stakeholder viewpoint, place, or time of study; timeliness is key; and outcomes rely on complex negotiations rather than linear logical arguments. Many of the agile methods and tools implicitly recognize this and respond to the situation.

Articles by Eitzinger and by Chelanga et al. present novel data collection approaches. Eitzinger's 5Q approach used interactive voice calls to ask only five questions to over 37,000 respondents. The five questions were selected using a decision tree system, which, through many individual calls, builds up a rich data resource covering a larger number of questions. Chelanga et al. described the Kaznet smartphone app, which was used by pastoralists to monitor livestock, grazing, and market conditions whilst they went around their daily business in Northern Kenya and Southern Ethiopia.

Five articles conducted analyses based on data derived from multiple implementations of agile tools. Milner et al., Marinus et al., and Caulfield et al. each compiled secondary data from previous implementations of the Rural Household Multi Indicator Survey (RHoMIS) (Hammond et al., 2017; van Wijk et al., 2020). Gotor et al. combined data from RHoMIS and the tricot approach (van Etten et al., 2019; Brown et al., 2022), while Teeken et al. combined data from RHoMIS and an application of the 1000 minds tool (Hansen and Ombler, 2008; Balogun et al., 2022). Another three articles collected novel data using the RHoMIS tool and presented analyses based upon that data (Alary et al.; MacLaren et al.; Périnelle et al.). van Vliet et al. and Harris et al. compiled large datasets from more traditionally implemented household surveys. All of this demonstrates the utility of following good practices in data management, and how effective design of data collection tools facilitates enhanced use of that data.

4. System transformation

The term "system transformation" is increasingly used in the context of sustainable development and agriculture research (e.g., CGIAR, 2021). Although a somewhat nebulous concept, it usefully articulates the outcome-oriented nature of the research. Analyses of system transformation generally focus on themes of resilience, robustness, rigidity, adaptability, and transformability (Zurlini et al., 2015; Meuwissen et al., 2019). System transformation (or transition) is complex, long-term, unpredictable, involves many sectors and stakeholders, and entails behavior change (Geels, 2002; Markard et al., 2020). Management of system transformations requires foresight and anticipation, the preparation of many necessary "ingredients," and the setting-up of "guardrails," so that when the various cumulative stimuli necessitate a transformation, it is more likely to be a favorable transformation.

Agile tools and methods can play a role supporting such transformations. The main route is by enhanced provision of useful and timely information to decision makers at multiple levels. The secondary route is by stimulating behavior change of researchers. The steps involved in the main route are: an improved and more collaborative data environment (Gorman et al.; Devare et al.; Kruseman); quicker and more efficient data collection (Eitzinger; Chelanga et al.); development of common analytics (e.g., for resilience, Alary et al.; or on poverty reduction; Harris et al.; van Vliet et al.; Marinus et al.); and delivery of actionable information to decision makers. While the whole chain is not evident in any one article, all of the constituents appear within this Research Topic collection. Perhaps Andrade et al. come the closest to describing the complete pipeline in a single application.

Different models for information flow are required for decision makers at the farm-level and at finer jurisdictional levels (e.g., for extension services). Périnelle et al. combine participatory agronomy and agile methods in Burkina Faso; Teeken et al. explore social differentiation factors for variety trait selection in Nigeria; and Gotor et al. report on citizen science variety testing in India. Milner et al. apply a spatial clustering technique to account for contextual drivers of dietary diversity in Southern Kenya; Caulfield et al. explore demographic factors and off-farm work to shed light on livelihood dynamics in the northern Andes; and MacLaren et al. explore how demographic features and assets influence decisions to diversify farms in Nigeria and Kenya. These studies all take account of local context to target specific interventions toward specific groups of people for greater impact and efficiency.

As these efforts to finesse development programming mature and the information flows become more routinely used, we should start to monitor the impacts on decision making. It will be important to show how information improves decision-making and contributes to system transformation.

5. Conclusions

This Research Topic collection provides a robust foundation to support future development of agile research tools to cut through the excess of data and deliver timely and actionable information. This is demonstrated by the emergence of common practices between many of the methods presented within this collection. We distill a list of features which agile research tools contain in differing combinations:

- Light-weight compared to traditional alternatives.
- Lean data—collect the least amount of information required for a specific goal.
- Accessible, intuitive, human-centered design.
- Adaptable to many geographic and project contexts.
- Elements of crowdsourcing.
- Data pipeline beyond collection—streamlined processing, analysis, and interpretation.
- Real-time or near-real-time data streams.
- Monitor real-world situations not controlled experiments.
- Embedded in real-life processes, such as a project cycle or business.

We expect that over time, experimentation with agile data-oriented research tools will provide more insights in the relative contribution of the different features to decision making and system transformation. Future studies should document their impact on the quality, timeliness, and granularity of decisions affecting system transformation.

Author contributions

JH wrote the initial draft of the editorial and proposed the Research Topic. All authors contributed to the manuscript and approved it. All guest editors contributed to the conceptualization of the topic and the soliciting and editing of manuscript.

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Conflict of interest

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Unpicking the Inter-relationships Between Off-Farm Livelihood Diversification, Household Characteristics, and Farm Management in the Rural Andes

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Rural households across the world are increasingly turning to off-farm sources of income to complement or replace farm income. A better understanding of these livelihood adaptations, their consequences, and the processes behind them will facilitate more effective rural development policies and projects. The objective of this research was to examine how off-farm income influences rural livelihoods, elucidate factors that determine different livelihood strategies, as well as understand how these livelihood strategies are associated with different approaches to farm management. Using data from 588 Rural Household Multi-Indicator Surveys (RHoMIS) in three rural Andean regions in Bolivia, Ecuador, and Peru, we identified a typology of farming household livelihood strategies, and assessed the differences among these household types with regard to household and farm level characteristics, and farm management. We found that among the household types that incorporated off-farm income into their livelihood strategies, there were significant differences in approaches to farm management. Specifically, we observed an increased use of industrialized farming techniques among one household type, a deintensification, or a stepping-out of farming activities in another household type, and a tendency toward livestock specialization in the other household type. Moreover, our findings revealed that household level characteristics (age and education level of head(s) of household, and household composition) played an important role in mediating which type of livelihood strategy the households employed. For example, "stepping-out" households generally had younger and more educated household heads. Location-specific factors such as access to markets, irrigation, and off-farm employment opportunities were also likely to be highly influential in terms of which pathways farming households adopted as their livelihood strategy. We conclude that rural development programmes and projects must be driven by the rural communities themselves taking into account this heterogeneity in household characteristics and livelihoods and engaging in the already advanced conversations around different approaches to farming and the conservation of common natural resources.

Keywords: off-farm income, out-migration, rural mobility, rural development, socio-ecological systems

HIGHLIGHTS

- Five hundred and eighty-eight rural household surveys were administered in Bolivia, Ecuador, and Peru.
- Households incorporating off-farm income employed diversified livelihood strategies.
- Livelihood strategies were associated with different approaches to farm management.
- Household head age and education level coupled with location determined livelihoods.
- Off-farm livelihood diversification has important implications for rural development.

INTRODUCTION

In the face of poverty and growing existential threats caused by climate change and land degradation, many rural households are turning to alternative, off-farm sources of income to complement or replace farm income. These off-farm income sources (e.g., construction, commerce, seasonal labor in the agricultural sector, or international migration) are accessed through growing opportunities for temporary and permanent forms of rural out-migration (McDowell and Hess, 2012; Zoomers, 2012; Brandt et al., 2016). Why some households employ one livelihood strategy rather than another, however, remains poorly understood (Gray and Bilsborrow, 2013). A better understanding of these adaptations and the processes behind them will inform more sustainable development strategies aimed at supporting impoverished rural households globally and especially in the developing world (Liu and Xu, 2016; Serrat, 2017).

One narrative that is growing in recognition suggests that, rather than regarding rural out-migration as a flow of people "moving out" of rural areas, it is better conceived as a livelihood adaptation strategy that builds webs of relationships to reduce vulnerability (Zoomers, 2012). Indeed, diversification of rural household livelihood strategies through the generation of off-farm income can prove to be an effective mechanism by which rural households are able to enhance their financial resources, enabling them to remain in the communities in which they grew up. Two recent studies provide important evidence for this insight. Ye (2018) found that rural "stayers" in China developed diversified livelihood strategies based on off-farm income involving multiple jobs and contributing significant amounts to their household livelihoods. While Mata-Codesal (2018) concluded that off-farm income constituted a critical part of complex life strategies that enabled rural households to remain in a village in Mexico.

While many studies focus on the main "external" drivers for livelihood diversification through enhanced rural mobility (Black et al., 2011; De Sherbinin et al., 2011; Gray and Bilsborrow, 2013; Greiner and Sakdapolrak, 2016), others have also highlighted the importance of family and household level characteristics that mediate these drivers of change to rural livelihood strategies. For example, in a recent study based on longitudinal interviews with 553 households in four rural sites in north-west Ethiopia, households with higher levels of education tended to assume livelihood strategies that incorporated long-term out-migration and therefore higher proportions of off-farm income (Tegegne and Penker, 2016). The age of the household head is another important factor that can influence livelihood strategies related to off-farm income generation through temporary migration, with younger household heads more likely to engage in off-farm employment (Carr, 2014; Dodd et al., 2016). Gender and marital status have also been reported to be significant factors (Radel et al., 2012; Carr, 2014; Gray and Bilsborrow, 2014), leading to a "feminization of agriculture," where women are becoming increasingly more engaged in agricultural production and decision-making as men participate more in rural out-migration (Deere, 2005; Lastarria-Cornhiel, 2006; Radel et al., 2012). However, it is important to point out that such trends are not universal. Indeed, in other contexts where off-farm employment opportunities are greater for women than men, the opposite pattern has been observed (McKay, 2005).

Beyond the processes that influence shifts in rural livelihood strategies are the implications of such changes for farm and land management. The growing opportunities presented by rural mobility and associated remittances to rural sending-households have been shown to be accompanied by important shifts in farm and land management (Li, 2013; Gray and Bilsborrow, 2014). However, despite a growing body of research on the subject, the impact of shifting livelihood strategies on farm management remains unclear. Many studies report contrasting effects in terms of adopting more industrialized farming techniques (e.g., agrochemical inputs, tillage) vs. more agroecological approaches as well as changing patterns in land degradation and land conservation (Geist and Lambin, 2002; Mendola, 2008; Gray, 2009; Angelsen, 2010).

For example, in a rural community in the central Ecuadorian Andean province of Cotopaxi, farming households with off-farm income displayed greater use of mechanized tillage, chemical fertilizers, and pesticides compared to households without off-farm income, raising concerns of land-use sustainability (Caulfield et al., 2019). In another study in the Philippines, the involvement of women in off-farm income activities led to the loss of more ecologically sustainable cropping patterns and a transition to more industrialized cropping systems

(McKay, 2005). At the same time, other studies suggest that off-farm income can be associated with farming deintensification. In Chongqing Municipality of Southwest China, households with important off-farm income sources cultivated smaller areas of land with fewer agricultural inputs (Qin, 2010). In another study in the south of Ecuador, households with livelihood strategies that included remittances from international migration tended to invest more in housing and land acquisition than in agricultural productivity (Jokisch, 2002).

These contrasting findings in the literature reveal that the direct and indirect socio-ecological relationships within each unique context and household are important for understanding the responses to broader pressures, their effects on livelihood strategies, and on farm and land management (Geist and Lambin, 2002; Caulfield et al., 2019). Livelihood strategies do not appear to vary in some direct and predictable way with farm management. Instead, distinct livelihood types appear to emerge from a complex set of factors that result in non-linear associations with farm management.

The case of rural communities in Latin America exemplifies many of the challenges of rural communities across the globe and the relationships discussed above. According to a report from the International Labor Organization (ILO), Latin America is the region with the greatest proportion of rural indigenous communities living in extreme poverty (Dhir et al., 2019). In parallel to the challenges posed by such poverty, rural communities in the Andes are also facing critical threats as a result of climate change, land degradation, decreases in agricultural productivity, and shifts in land tenure systems (Perez et al., 2010; Fonte et al., 2012), thus increasing their vulnerability (Montaña et al., 2016). As such, there is a growing trend for rural households in the Andes to assume different livelihood strategies that incorporate off-farm income (Perez et al., 2010; Valdivia et al., 2010; Zimmerer and Vanek, 2016). The objective of this research was therefore to provide greater insight into the influences of increased rural mobility and off-farm income on rural livelihoods in a number of rural communities spread throughout the Andes. Additionally, we sought to elucidate some of the factors that determine different livelihood strategies, as well as understand how different livelihood strategies are associated with different approaches to farm management.

MATERIALS AND METHODS

Conceptual Framework

As conceptualized in **Figure 1**, we hypothesize that: (1) farming household livelihood strategies (defined by a series of farm production and off-farm income activities) are associated with significant differences in farm management approaches; (2) farming household livelihood strategies are associated with differences in household characteristics (e.g., composition, age, education level); and (3) relationships between household and farm level characteristics are context dependent.

Study Sites

In Bolivia (**Figure 2**), the surveys were conducted between September and November 2018 in two administrative "departments" or regions (Chuquisaca and Cochabamba) and three municipalities (Villa Serrano and Alcalá which form part of the Chuquisaca region, and Mizque which pertains to the region of Cochabamba), in the central and southern Andes of Bolivia. The elevation range for the communities in which the surveys were administered was between 1,400 and 2,500 masl, while the average annual temperature varied between a

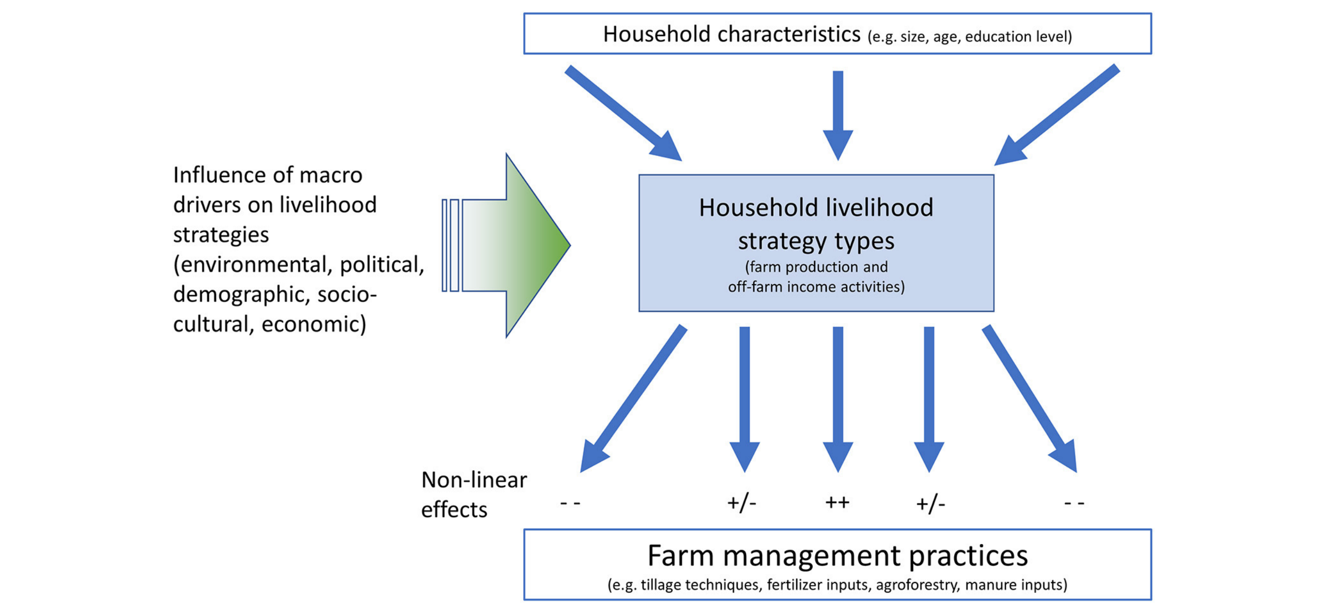

FIGURE 1 | Conceptual model outlining the relationships between rural household characteristics, livelihood strategy diversification, and farm management.

FIGURE 2 | Geographical location of the study sites. Red pins indicate capital cities, blue pins indicate study sites.

low of 16.1°C in a community in Alcalá and a high of 20.6°C in a community in Villa Serrano. Annual precipitation also varied considerably (400–950 mm year^{-1}). There is a dry season from May to October and a rainy season from November to April. According to the local rural development institution that administered the rural household survey, farming systems in the region are mostly small-scale mixed livestock-cropping systems. The main crops cultivated in the region are maize (*Zea mays*), peanuts (*Arachis hypogaea*), potato (*Solanum tuberosum*), bean (*Phaseolus vulgaris*), and wheat (*Triticum aestivum*). Onions (*Allium cepa*), peas (*Pisum sativum*), and fruit trees are also commonly cultivated in Mizque and Villa Serrano. The dominant crop rotation comprises of peanuts, followed by potatoes, and then maize. Small-scale livestock production for home consumption and sale are common, with most households owning some cattle (also used as draft-animals), pigs, and chickens. Sheep are also commonly reared in Alcalá and Mizque. Many households in Alcalá have access to irrigation supplied by rivers or rain water harvesting ponds, but there is no access to irrigation water in Villa Serrano, and only between 10 and 40% of rural households have access to irrigation water in Mizque. Communities surveyed in Alcalá varied in distance to the main municipal market, ranging from 10 to 30 km. Communities in Mizque were located 35–45 km from the municipal agricultural market, while communities in Villa Serrano were located between 20 and 70 km from the municipal agricultural market.

The rural household surveys administered in Ecuador (**Figure 2**) were undertaken between September and October 2018 in four municipalities (Latacunga, Pujili, Salcedo, and Saquisilí) pertaining to the administrative region of Cotopaxi, in central Ecuador. The municipalities are located at elevations between 2,552 and 3,890 masl with temperatures generally ranging between 5 and 20°C. Average annual precipitation rates also vary substantially between 500 and 1,000 mm year^{-1}, with a drier period between June and September and a wetter period between October and May. Farming practices normally comprise of small-scale, mixed livestock-cropping systems. Maize, potato, and forage crops such as barley (*Hordeum vulgare*), vetch (*Vicia sativa*), oats (*Avena sativa*), and alfalfa (*Medicago sativa*) are the dominant crops in the area with most small-scale farming households rotating crops annually or biannually, often concentrating agricultural inputs during the potato crop cycle. Small numbers of cattle are often raised for milk production for self-consumption and for sale to local traders. Cattle are also used for draft power in many households. Other livestock reared for home consumption or sale include sheep, pigs, chickens, and guinea pigs. Access to irrigation varies considerably community by community, with around 70% of rural households having access to irrigation water in Salcedo, but only 26% in Saquisilí. Market access is also highly variable among locations (between 15 and 70 km to district markets) with better transport infrastructure and services to market found in the municipalities of Latacunga and Salcedo, but poorer market access in Pujili.

Finally, the rural household surveys administered in Peru (**Figure 2**) were undertaken between February and March 2018 in three central Andean municipalities (or provinces) (Huamanga, Acobamba, and Huancayo) pertaining to the administrative regions of Ayacucho, Huancavelica, and Junín, respectively. The communities in which the surveys took place ranged in elevation from 2,800 to 4,500 masl, varying in annual average precipitation between 700 and 1,200 mm year^{-1}, with a wetter period between September and March and a drier period between April and September. As the highest of the three main locations surveyed, the communities in the three municipalities of Peru are also the coldest with average annual temperatures between 9 and 15°C, with temperatures regularly falling below freezing at higher elevations. Farming practices normally comprise of small-scale, mixed livestock-cropping systems. Potato, barley, oats, broad beans (*Vicia faba*), quinoa (*Chenopodium quinoa*), and a variety of Andean tubers [Oca (*Oxalis tuberosa*), Olluco (*Ullucus tuberosus*), and Mashua (*Tropaeolum tuberosum*)] are the dominant crops in the area with most small-scale farming households rotating crops annually or biannually. Multi-year fallow periods within crop rotations remain commonplace in these rural areas of Peru, especially at higher elevations, where fallow periods tend to be even longer (Vanek et al., 2020). Agricultural inputs are often concentrated during the potato phase of the rotation. Cattle, sheep, llamas, and guinea pigs are raised for meat and wool production for self-consumption and for sale to local traders and at markets. Cattle are also used for draft power in many households. Access to irrigation varies considerably between and within communities, with no more than 50% of rural households in each community having access to irrigation water. Access to regional markets is challenging due to distances (up to 125 km) and poor road infrastructure (often only dirt roads for parts of the journey near the communities) and irregular transport services.

Survey Design and Data Collection

The data was collected from the three countries using the Rural Household Multi-Indicator Survey (RHoMIS), a standardized farm household survey used in rural development contexts, and covering topics such as household characteristics, agricultural management and production, livelihoods, and decision making (Hammond et al., 2017; van Wijk et al., 2020; **Table 1**). The survey was tailored to the local context and was applied to 588 farming families across three countries: Bolivia (134 households), Ecuador (284 households), and Peru (170 households) (**Table 2**).

The rural locations for the household surveys formed part of the activities of a group of participating grantees of the Collaborative Crop Research Program of the McKnight Foundation (https://www.ccrp.org/), that jointly decided to assess household level characteristics and farm management for some of the communities in which they are engaged. The study sites selected reflect the great heterogeneity of socio-economic and agroecological rural contexts in the Andes. By compiling data in these disparate contexts in the Andes, it was hoped that the findings of the research would be more generalizable for the broader Andean and global context in developing countries. The sites could be characterized as representing a gradient of farming household market orientation, with the communities surveyed in Bolivia displaying greatest market orientation, and the communities in Peru representing farming households with lower levels of market orientation and with more subsistence farming. The rural communities surveyed in Ecuador could be seen as an intermediate context of these two situations. The study sites also aimed to reflect a broad range in contexts in terms of distance and access to urban areas and agroecological conditions. In this respect, the communities of Ecuador were generally located much closer and with better access to urban areas compared to the other two sites. Meanwhile, the communities in Peru tended to be located at much higher elevations, and the communities in Bolivia were located at lower elevations.

We note that the surveys were undertaken in communities in which NGOs were active and not actively selected for the specific goals of this study. As such it is important to acknowledge potential sources of bias associated with site selection or NGO impact when interpreting the results and conclusions of the research.

Given that the household surveys were developed to address specific objectives of already existing projects, sampling methodology varied among study sites accordingly. In Bolivia and Peru, sampling was undertaken using randomized sampling techniques of households based on lists of households in each community. In Ecuador on the other hand, a geographically stratified sampling strategy was used, based on grid locations developed using GIS software across the project area. The farming household located at the center of each of the geographical grid points were requested to participate in the survey. In the cases that the household refused to participate a neighboring household was asked instead.

While measurement errors are often a common limitation in household surveys (Fraval et al., 2020), these were minimized by using electronic data collection techniques that had been trialed in the study sites before commencing the surveys. Moreover, the rural household survey administered (RHoMIS) has now been trialed in more than 33 countries and has therefore undergone a number of adaptations to ensure as few measurement errors as possible through a survey validation process built in to the survey (van Wijk et al., 2020). The survey has also been designed to be as rapid as possible to avoid fatigue of the individuals answering on behalf of the households (average time 40–60 min) (Hammond et al., 2017).

Data Analysis

To create the livelihood strategy household typology Ward's method of hierarchical clustering (Ward, 1963) was applied to the data of households that either: (1) incorporated off-farm income into their livelihood strategy, or (2) did not incorporate off-farm income into their livelihood strategy. The variables included in the clustering analysis included farm production variables, and the off-farm income activities variables for those

TABLE 1 | Description of variables collected by the RHoMIS survey used to assess the associations between household characteristics, farm production, and farming management collected in rural Andean communities in three South American countries.

Variable (unit)	Variable type	Description
HOUSEHOLD CHARACTERISTICS		
Age of female household head (years)	Continuous	Mean age of the female head
Age of male household head (years)	Continuous	Mean age of the male head
Age of household head(s) (years)	Continuous	Mean age of the head(s) of household combined
Household size (number of persons)	Continuous	Size of household
Household labor availability (number of persons above 10 years old)	Continuous	Size of household minus children aged 10 and under
Education level (highest education level of the head(s) of household)	Ordinal	0 = no education; 1 = primary education; 2 = secondary education; and 3 = post-secondary education
Household head composition (single or couple)	Binary	Single household head (0); two heads of household or couple (1)
OFF-FARM ACTIVITIES		
Off-farm income count (members of household engaged in off-farm activities)#	Continuous	Number of household members engaged in off-farm income activities
Off-farm income proportion (%)#	Continuous	Estimation of proportion of total household income from off-farm income activities
Participation in high value off-farm income (highest value level of off-farm income activities)†#	Ordinal	No off-farm employment activities (0); only very basic menial off-farm employment such as local farm laborer (1); salaried off-farm employment or skilled labor employment (e.g., governmental employee, maid, transport, shop keeper) (2)
FARM PRODUCTION		
Farm income (US$ year^{-1})#	Continuous	Total amount of cash generated by farm sales (based on reported annual production and sales of crops and livestock)
Cropping market orientation (proportion of crops sold)#	Continuous	Proportion of annual crops produced that are sold to market
Crop sales (US$ year^{-1})	Continuous	Income generated from crop sales
Crop value ha (US$ year^{-1} ha^{-1})	Continuous	Crop production expressed in US$ a year per ha per farm
Land cultivated (ha)#	Continuous	Amount of land available for the farming household to cultivate
Value crop produce (US$ year^{-1})#	Continuous	Crop production expressed in US$ a year per farm
Livestock market orientation (proportion of livestock sold)#	Continuous	Proportion of annual livestock products that are sold to market
Livestock product sales (US$ year^{-1})	Continuous	Income generated from sales of livestock and livestock products
Value livestock production (US$ year^{-1})#	Continuous	Livestock production expressed in US$ a year per farm
Livestock holdings (TLU)#	Continuous	Total livestock holdings (all farm animals)
FARM MANAGEMENT		
Mechanized tillage (usage)	Binary	No reported use of mechanized tillage (0); reported use of mechanized tillage (1)
N fertilizer inputs (kg N year^{-1} ha^{-1})	Continuous	Reported amount of nitrogen applied on farm through chemical fertilizers
Pesticide use (usage)	Binary	No reported use of pesticides (0); reported use of pesticides (1)
Agroforestry (proportion of farming households)	Binary	No reported use of agroforestry (0); reported use of agroforestry (1)
Manure inputs (usage)	Binary	No reported use of manure (0); reported use of manure (1)
Crop rotation (usage)	Binary	No reported use of crop rotation (0); reported use of crop rotation (1)
Legume rotation to enhance soil fertility (usage)	Binary	No reported use of legumes (0); reported use of legumes (1)
Crop diversity (count)	Continuous	Number of crop varieties cultivated
Livestock diversity (count)	Continuous	Number of livestock species kept

† *See Appendix 1—**Supplementary Table 1** for an overview of the higher value income employment observed in the surveys.*
# *Variables input into BCA for development of livelihood household typology.*

households incorporating off-farm income into their livelihood strategies (**Table 1**). Due to strong correlations between some of the crop production (crop sales, crop value ha, and value crop produce) and livestock production variables (livestock product sales, value livestock production), crop sales, crop value per hectare, and livestock product sales were removed from the analysis. Using clustering tree diagrams, the number of household livelihood strategy types created for farm-focused household livelihoods (not incorporating off-farm income) was four. For households incorporating off-farm income, three household types were created.

To further visualize and test for differences among livelihood strategy types, a between class principal component analysis (PCA) was applied to each of the sets of household typologies (farm-focused households and with off-farm income) using the same variables as the cluster analysis. A Monte Carlo between

TABLE 2 | Number of rural household livelihood strategy types by country (followed by percentage in parenthesis).

Location	Household type						
	Farm-focused (FF)				Off-farm income (OF)		
	FF 1—livestock specialists	FF 2—commercial farms	FF 3—crop specialists	FF 4—subsistence	OF 1—mixed livelihoods	OF 2—mixed livestock specialists	OF 3—stepping-out
All sites	157 (27%)	69 (12%)	112 (20%)	68 (12%)	100 (17%)	39 (6%)	43 (7%)
Bolivia	19 (14%)	53 (40%)	1 (<1%)	55 (41%)	5 (4%)	1 (<1%)	0 (0%)
Ecuador	97 (35%)	15 (5%)	56 (20%)	45 (16%)	15 (5%)	25 (9%)	28 (10%)
Peru	41 (24%)	1 (<1%)	55 (32%)	23 (14%)	27 (16%)	9 (5%)	14 (8%)

class PCA test was also applied to assess for significant differences among household livelihood strategy types.

Individual mixed error component models were then applied, including "country" as a fixed effect and nested random effects for "region" and "municipality" in order to account for location-specific effects, to assess differences among livelihood strategy types in terms of farm production, off-farm income activities, household characteristics, and farm management variables. Fisher's least significant difference tests were applied to examine the differences among livelihood strategies, such that livelihoods with different letters were found to have different estimated marginal means at the 5% significance level.

Assumptions of homoscedasticity and normality were tested for all continuous variables and data transformed as needed using the log function. All analyses were carried out within the RStudio environment version 1.2.1335 for R (version 3.6.1) using ade4, agricolae, lmerTest and emmeans packages.

RESULTS

Livelihood Strategy Typology Development and Characterization

The hierarchical clustering identified three livelihood strategy types incorporating off-farm income (OF1, OF2, OF3), and four livelihood strategy types that did not incorporate off-farm income, or farm-focused livelihood strategies (FF1, FF2, FF3, FF4). The number of households falling in each livelihood strategy ranged from 39 households in OF2 to 157 households in FF1. While generally there was a fairly proportional distribution of the livelihood strategy types in the rural communities in Ecuador and Peru with the exception of FF2 in Peru which only had one household, in Bolivia household livelihood strategies were dominated by FF2 and FF4 livelihood strategies (**Table 2**).

The between class PCA confirmed significant differences among livelihood strategy types (Monte Carlo test based on 999 replicates, $p = 0.001$). For the livelihood strategy types incorporating off-farm income, Principal Component 1 (PC1) accounted for 35% of variance, while Principal Component 2 (PC2) accounted for 18% of variance. OF1 and OF3 livelihood strategies differed primarily along PC1. While OF1 was more positively correlated with variables associated with farm production such as value crop production, land cultivated, farm income, livestock holdings, and crop market orientation, OF 3 correlated positively with proportion of off-farm income and value of off-farm activities. OF2 differed to OF1 and OF3 along PC2. OF2 livelihood strategies correlated most strongly with livestock market orientation. Proportion of off-farm income, value of off-farm activities, off-farm incomes count, and livestock value production also positively correlated with OF2 (**Figure 3A**).

For farm focused livelihood strategy types, PC1 accounted for the greatest variance among livelihood strategy types (73%), while PC2 accounted for 23% of variance. FF1 and FF2 differed from FF3 and FF4 primarily along PC1. Both FF1 and FF2 correlated more with all the farm production variables (crop market orientation, livestock holdings, livestock market orientation, livestock value production, farm income, land cultivated, and crop value production). FF1 differed to FF2 along PC2. FF1 correlated more with livestock market orientation and value livestock production, while FF2 correlated more with value crop production, land cultivated, and farm income (**Figure 3B**).

The mixed error component model analyses showed that the FF2 household livelihood strategy type displayed the highest levels in nearly all the farm production variables analyzed (farm income, crop market orientation, crop sales, crops value, land cultivated, value of crop produce, value of livestock production, and livestock holdings). The only variable in which it did not display the highest levels was livestock market orientation. Given these results, one could characterize these households as "commercial farms." The livelihood strategy that displayed the lowest in nearly all the farm production variables was FF4. The only two variables where FF4 did not display the lowest levels was for crop value per ha and livestock market orientation, although for both of these variables the levels were not statistically different from the types with the lowest levels. These farming households could therefore be interpreted as "subsistence" farming households. The differences between FF1 and FF3 appeared to be borne out in their differences in whether their focus was orientated toward livestock or agricultural crop production. FF3 households in particular displayed among the lowest levels of livestock production suggesting that they were more oriented toward agricultural crop production ("crop specialists"). FF1 households on the other hand displayed among

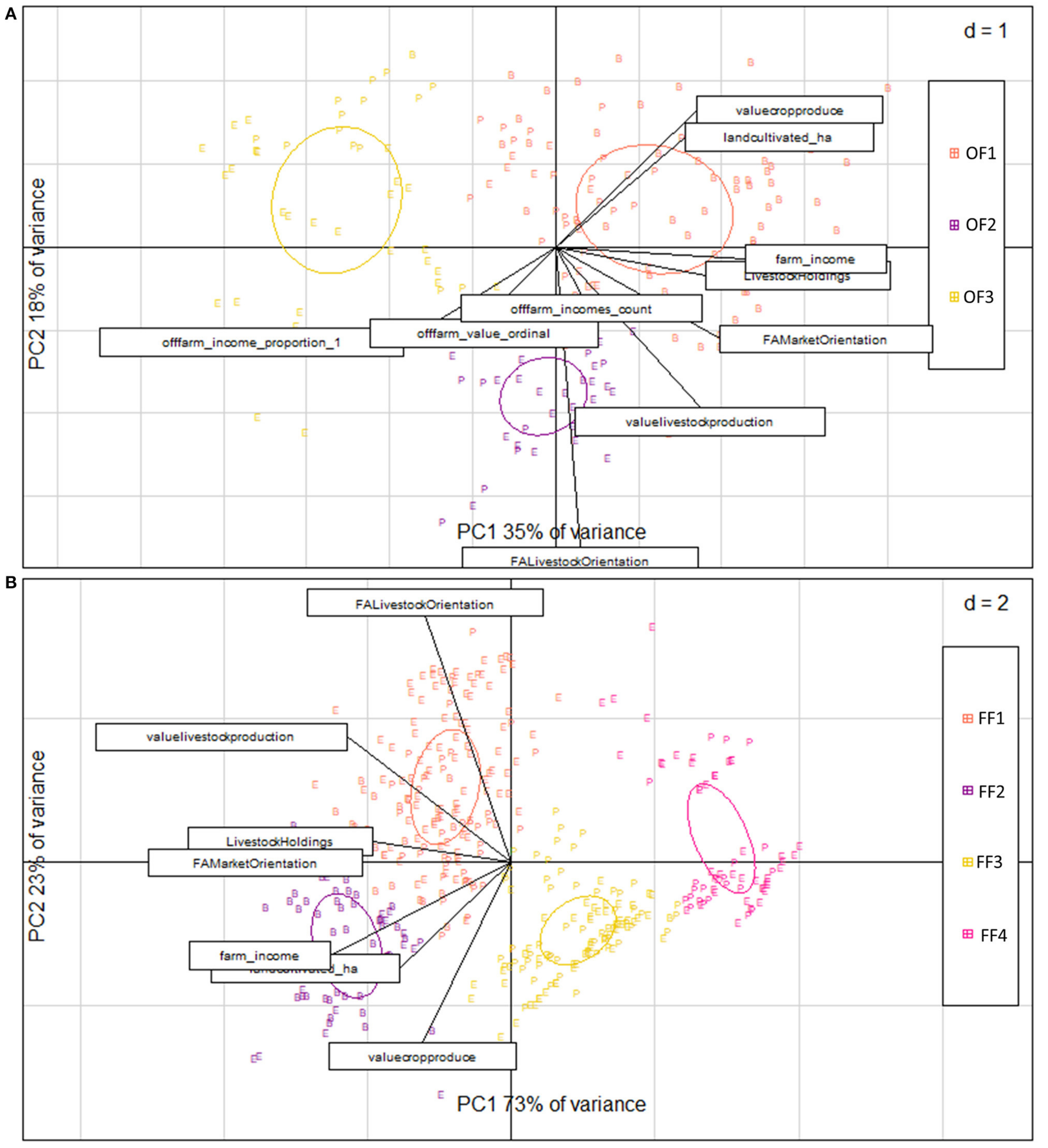

FIGURE 3 | Between class principal component analysis assessing correlations between farm production and household livelihood strategy types. **(A)** Livelihood strategies that incorporated off-farm income. **(B)** Farm-focused livelihood strategies. Letters correspond to country location of household (B = Bolivia, E = Ecuador, P = Peru). Ellipses correspond to livelihood strategy defined by hierarchical clustering (**Table 2**).

the highest levels for most livestock production variables and therefore could be viewed as "livestock specialists" (**Table 3**).

Among the households with off-farm income incorporated into their livelihood strategies, OF1 households generally displayed the highest levels of farm production variables for agricultural crop production, and relatively high levels of livestock production. For the off-farm livelihood variables, OF1 exhibited the smallest proportion of off-farm income and the

TABLE 3 | Estimated marginal means for farm production variables of the different household livelihood strategy types#.

Variable	FF1—livestock specialists	FF2—commercial farms	FF3—crop specialists	FF4—subsistence	OF1—mixed livelihoods	OF2—mixed livestock specialists	OF3—stepping-out
Farm income	809 (193)d	5,988 (3,230)e	254 (68)c	<1 (<1)a	1,282 (368)d	394 (139)c	3 (1)b
Crop market orientation	0.7 (0.03)d	0.85 (0.04)e	0.5 (0.04)c	0.0 (0.04)a	0.72 (0.04)d	0.64 (0.05)d	0.19 (0.05)b
Crop sales	28 (9)c	6,311 (3,667)f	161 (61)d	<1 (<1)a	904 (353)e	5 (3)b	1 (1)b
Crop value ha	327 (68)ab	868 (264)c	392 (88)ab	278 (78)ab	461 (107)b	227 (72)a	343 (106)ab
Land cultivated	2.5 (0.3)b	4.9 (0.8)d	2.4 (0.3)b	1.2 (0.2)a	3.3 (0.4)c	1.5 (0.3)a	1.2 (0.2)a
Value crop produce	774 (100)c	3,316 (1,042)e	869 (127)c	229 (44)a	1,433 (227)d	330 (71)ab	386 (83)b
Livestock market orientation	0.51 (0.02)d	0.12 (0.03)bc	0.01 (0.03)a	0.06 (0.04)ab	0.17 (0.03)c	0.63 (0.04)e	0.07 (0.04)abc
Livestock product sales	756 (152)b	1,586 (186)c	98 (162)a	62 (178)a	543 (163)b	702 (198)b	42 (196)a
Value livestock production	478 (123)c	405 (150)c	<1 (<1)a	<1 (<1)a	61 (18)b	536 (227)c	<1 (<1)a
Livestock holdings	4.30 (0.5)c	6.32 (0.91)d	2.26 (0.3)b	1.24 (0.21)a	3.79 (0.44)c	3.39 (0.54)c	1.57 (0.29)ab

*Standard errors are presented in parentheses and results from Fisher's least significant difference test are indicated by lower case letters next to standard errors, such that livelihoods with different letters have different estimated marginal means at the 5% significance level. See **Table 1** for description of variables and units.*

second lowest number of household members participating in off-farm livelihood activities. OF1 households also had the lowest value of off-farm activities, indicating that the off-farm activities that these households engaged in tended to be more basic menial labor (i.e., at a local farm or unskilled construction). These households could be said to have "mixed livelihoods." OF2 households on the other hand displayed among the highest levels of livestock production for value of livestock production, livestock market orientation, and livestock product sales. Livestock holdings were also comparable to OF1 and FF1, the farm-focused livestock specialists. For the off-farm livelihood variables OF2 exhibited the highest number of members of household undertaking off-farm livelihood activities. These households also displayed among the highest value in their off-farm activities, meaning that they were more likely to be work as a governmental employee, driver, shop-keeper, etc. (see **Supplementary Table 1** for an overview of off-farm activities that were considered to be higher-value). As such, these households were coined "mixed livestock specialists." Finally, OF3 households displayed often similarly low levels in the farm production variables as FF4, the subsistence households. However, for the off-farm livelihood variables these households displayed the highest proportion of off-farm income. They also had the joint highest value for their off-farm income activities (along with OF2) meaning that the off-farm income activities were more likely to be work such as a governmental employee, driver, shop-keeper (as indicated in **Supplementary Table 1**). It is noteworthy that these households displayed the fewest members of the household participating in off-farm activities. Given the low farm production levels and the highest proportion of off-farm income, the livelihood strategy for these households could be perceived as "stepping-out" of farming (**Tables 3**, **4**).

TABLE 4 | Estimated marginal means for off-farm income activity variables of the different household livelihood strategy types incorporating off-farm income activities#.

Variable	Livelihood strategy type		
	OF1—mixed livelihoods	OF2—mixed LS specialists	OF3—stepping-out
Off-farm income count (number of members of household engaged in off-farm activities)	1.1 (0.02)b	1.2 (0.03)c	1.0 (0.03)a
Off-farm income proportion	0.3 (0.02)a	0.5 (0.02)b	0.6 (0.02)c
Participation in high value off-farm income	1.2 (0.05)a	1.5 (0.06)b	1.5 (0.06)b

*Standard errors are presented in parentheses and results from Fisher's least significant difference test are indicated by lower case letters next to standard errors, such that livelihoods with different letters have different estimated marginal means at the 5% significance level. See **Table 1** for description of variables and units.*

Household Characteristics and Livelihood Strategy Types

The subsistence livelihood strategy household type had the oldest household heads, 58 years, while the stepping-out livelihood strategy household type had the youngest household heads, being on average 15 years younger (43 years). Similarly, for education level of household heads the biggest difference between livelihood strategy types was found between stepping-out livelihood strategy households, having the highest average education level (at least 30% having completed primary education), and subsistence livelihood strategy households, who had the lowest education level attainment with only 7% completing primary school. Subsistence households also comprised the highest number of single household heads, while the household livelihood strategy types that incorporated off-farm income generally had most household heads that were a couple. Livestock specialists, crop specialists, and mixed livelihood households were the smallest households (3.91, 3.77, and 3.94 persons, respectively), while mixed livestock specialists were the largest (4.81 persons).

Livelihood Strategies and Farm Management Techniques

Farm management variables associated with more industrialized approaches to farming such as mechanized tillage, and the use of chemical fertilizers and pesticides were used more by farm focused livestock specialists, commercial farms, and crop specialists households, and by mixed livelihood households. Notably, mixed livelihood households applied nearly 60% more chemical fertilizers than any other household livelihood strategy type; they were also the second most likely to use pesticides and mechanized tillage, slightly less than the commercial farming households. Subsistence and stepping-out livelihood strategy types on the other hand consistently were the least likely households to employ these types of farming practices (**Table 6**). In relation to agroecological techniques for agricultural intensification, while the commercial farms were the most likely to employ agroforestry practices, they were also the least likely to use manure inputs, crop rotation, or the rotational planting of legume crops to enhance productivity. Subsistence households were the most likely to use manure inputs, while mixed livestock specialists were the most likely to rotate crops and use legume crops as part of the rotation. Crop diversity tended to be highest in the farm-focused livestock specialists, commercial farms, and crop specialists households, and by mixed livelihood households. It was lowest for subsistence household types, which also had the lowest levels of livestock diversity, while mixed livestock specialists tended to have the greatest livestock diversity (**Table 6**).

DISCUSSION

Off-Farm Income, Livelihood Diversification, and Farm Management

Households in these rural Andean contexts have developed distinct livelihood strategies that are associated with significantly different approaches to farm production and management. Among farm households without any off-farm income, four livelihood strategy types emerged: commercial farms, livestock specialists, crop specialists, and subsistence farms. Among households that derived part of their income from off-farm sources three main livelihood strategy approaches emerged: one that remained focused on commercial farm production activities and that generated significant amounts of off-farm income in parallel (mixed livelihoods); another household type that mixed their off-farm livelihood activities with an on-farm specialization in livestock production (mixed livestock specialists); and a third type that appeared to be stepping-out of farming activities, generating the majority of income from off-farm sources and dedicating most farming activities to self-consumption (stepping-out).

One of the striking findings from this study was that households that incorporated off-farm income exhibited a similar diversity in terms of livelihood strategies among households as those that did not incorporate off-farm income (**Figure 3**; **Tables 3**, **4**). Moreover, this diversity in livelihood strategies among households incorporating off-farm income was also associated with significant differences in terms of farm management. Specifically, our findings revealed that among farming households that generated off-farm income, mixed livelihood household types displayed the greatest use of industrialized farming techniques (**Table 6**). These households also applied 60% more chemical fertilizers than any household types focused on farm production as their sole source of income. Overall, they were also the second most likely household type to use pesticides and mechanized tillage, slightly less than the farm-focused commercial farms. In terms of farm production, mixed livelihood types also exhibited among the highest levels of market orientation and value production (**Table 3**), often having the second highest levels for these variables, only just a little less than commercial farm households, but higher than the other farm-focused household types. These findings suggest that mixed livelihoods households may be opting to invest some of their financial resources gained from off-farm income in industrialized farming techniques. This reflects the findings of others who have reported a positive correlation between off-farm income and the use of more industrialized farming techniques (Gray and Bilsborrow, 2014; Bhandari and Ghimire, 2016; Caulfield et al., 2019).

Furthermore, out of the household livelihood strategies that generated off-farm income, mixed household types generated less of their overall income from off-farm activities (30%) compared to mixed livestock specialists (50%) and stepping-out households (60%). The type of off-farm activity undertaken by mixed livelihood households was also more likely to be menial labor (i.e., farm hand or unskilled construction worker; **Table 4**). This further supports the idea that these households may be simply using off-farm activities to generate more financial resources in order to re-invest in their farming activities.

At the other end of the spectrum, stepping-out households generally displayed significantly lower levels for farm production and industrialized farming techniques variables, not dissimilar to farm-focused "subsistence" households (**Tables 3**, **6**), confirming the idea that farm production was only a supplemental activity aimed at meeting a self-consumption objective. In this respect our findings corroborate the work of other authors who suggest an association between off-farm income and farming deintensification (e.g., Jokisch, 2002; Benayas et al., 2007). It is likely that in contexts where the income generated from off-farm sources is sufficient and of high enough value, there is a lower dependency on agriculture and local natural resources for livelihoods and therefore a trend toward farming deintensification (Qin, 2010).

This relationship between high value off-farm income generation and farm deintensification is further supported by the fact that while stepping-out households generated the greatest proportion of off-farm income of their total income (60%), the average number of household members engaged in off-farm activities, was lowest among the three livelihood strategy types that undertook off-farm activities (**Table 4**). This suggests that the income generated by their off-farm activities was disproportionally higher per household member engaged in off-farm activities despite the fact that mixed livelihood specialists exhibited the same levels of participation in high-value off-farm income activities, enabling them to rely less on on-farm income. Unfortunately, further detail related to off-farm income activities were not available from the household surveys to be able to assess these relationships in greater depth. Further research on the relationships between farm production and management, and the nature and value production of off-farm income activities is therefore highly recommended.

Finally, off-farm livestock specialists represented a household type that appeared to mix significant amounts of off-farm activity with a specialization in livestock production, displaying similar levels of farm production as the farm-focused livestock specialist households, and with similarly low levels of agricultural inputs whether industrial or more agroecological (**Tables 4**, **6**). Again, this relationship between off-farm income generation and farm production and management is reflected in the scientific literature. For example, in a study undertaken in Bukina Faso, larger amounts of off-farm income from international remittances stimulated livestock production (Wouterse and Taylor, 2008).

These results provide a potential explanation for the often contrasting findings on the effects of off-farm income on farm management, where off-farm income has led to different scenarios at the farm level such as an increased use in industrialized farming techniques or an overall deintensification of farming activities (Jokisch, 2002; Gray and Bilsborrow, 2014; Tegegne and Penker, 2016). Specifically, as opposed to the linear relationships between off-farm income and farm management often presented in the scientific literature, here we observe the emergence of three different approaches to farming associated to different livelihood strategy types.

As hypothesized (**Figure 1**), when comparing these three household livelihood strategies, we cannot conclude that the generation of off-farm income is linearly associated with deintensification of farming activities and consequent re-establishment of non-agricultural land uses. This might be expected due to the potential decrease in access to labor resources, posited by the Forest Transition Theory (Rudel et al., 2005). In fact, as hypothesized by the theory of New Economics of Labor Migration, off-farm income generation can have a countervailing effect on the loss of labor resources (Taylor, 1999). Increases in financial resources from off-farm income are often positively associated with the use of industrialized agricultural inputs such as mechanized tillage, chemical fertilizers and pesticides (Davis and Lopez-Carr, 2010; Greiner and Sakdapolrak, 2013; Gray and Bilsborrow, 2014), and have even been used to address labor constraints through the hiring of extra labor from neighbors or local migrants (Zimmerer, 2014).

These differences between household livelihood strategies that generate off-farm income is an important finding, as it suggests that not only is the association between off-farm income and farm management non-linear, but that enhanced rural mobility and access to off-farm income opportunities enables further livelihood diversification. In fact, it appears that the generation of off-farm income can provide for diversified forms of livelihood strategies that enable rural households to "remain" (Zoomers, 2012; Mata-Codesal, 2018; Ye, 2018). However, it is important to point out, as argued in Caulfield et al. (2019) and Zimmerer and Vanek (2016), shifts in livelihood diversification pathways that involve the use of more industrialized forms of farming could pose long-term challenges to the sustainability of farming in these rural Andean landscapes due to land degradation.

Livelihood Strategies, Rural Household Characteristics, and Context Dependency

It is striking that stepping-out households represented the youngest and most educated households among all seven livelihood strategy types (**Table 5**). This is an important finding that corroborates the reports from inhabitants across the communities studied here, suggesting that the young are stepping-out of farming both permanently, through permanent out-migration, and economically, as those young households that remain tend to be deintensifying their farming activities. These results also reflect other studies that suggest that household characteristics are associated with different livelihood strategies (Carr, 2014; Dodd et al., 2016; Lopez-Carr et al., 2017).

TABLE 5 | Estimated marginal means for household characteristics of the different household livelihood strategy types[#].

Variable	Livelihood strategy type						
	FF1—LS specialists	FF2—commercial farms	FF3—crop specialists	FF4—subsistence	OF1—mixed livelihoods	OF2—mixed LS specialists	OF3—stepping-out
Age female head	51.3 (1.4)bc	44.0 (2.1)a	52.7 (1.6)cd	56.1 (2.0)d	47.3 (1.6)ab	48.0 (2.4)abc	42.9 (2.4)a
Age male head	54.3 (1.5)c	45.0 (2.1)a	55.0 (1.8)cd	59.7 (2.2)d	50.0 (1.7)b	45.9 (2.5)ab	43.8 (2.5)a
Age HH head	52.8 (1.4)c	44.7 (2.1)ab	54.0 (1.6)cd	57.7 (1.9)d	48.6 (1.6)b	46.9 (2.4)ab	42.8 (2.4)a
Education ordinal	0.9 (0.06)ab	1.2 (0.09)cd	0.9 (0.07)a	0.7 (0.09)a	1.1 (0.07)c	1.1 (0.10)bc	1.4 (0.10)d
HH size	3.9 (0.2)a	4.6 (0.3)ab	3.8 (0.3)a	4.0 (0.3)ab	3.9 (0.3)a	4.8 (0.4)b	4.1 (0.4)ab
HH head composition (proportion couple)	0.76 (0.04)ab	0.89 (0.04)cd	0.77 (0.05)abc	0.67 (0.07)a	0.92 (0.03)d	0.94 (0.04)d	0.89 (0.05)bcd

[#] *Standard errors are presented in parentheses and results from Fisher's least significant difference test are indicated by lower case letters next to standard errors, such that livelihoods with different letters have different estimated marginal means at the 5% significance level. See* ***Table 1*** *for description of variables and units.*

Education in particular appears to be playing an important role in enabling younger households to engage in higher value off-farm income. It is likely that there is an important link between average age of heads of household, education level, and the participation in high-value off-farm income activities (Tegegne and Penker, 2016). In this respect, younger households in rural communities in the Andes may be taking advantage of the opportunities presented by their improved education levels and enhanced access to high-value off-farm income sources. As they do so they may also be building networks that decrease their vulnerability in the face of important socio-environmental challenges, such as climate change and poverty (Zoomers, 2012).

At the other end of the spectrum, it is also noteworthy that households with subsistence livelihood strategies tended to be older and less educated than the other households. Furthermore, reflecting the findings of Carr (2014), these rural households also exhibited a higher proportion of single heads of household (**Table 3**). These findings potentially indicate the greater vulnerability of these households due to their lower human capital and therefore lower capacity to adapt their livelihood strategies in the face of changing socio-environmental conditions (Reza Shahraki et al., 2017; Shikuku et al., 2017; Odhiambo et al., 2019). We also need to consider the possibility that stepping-out and subsistence household types represent instances in a rural household's lifecycle, where household livelihood strategies evolve over a household's family lifecycle in order to adapt to different opportunities and challenges related to changes to human capital. This idea fits with the rural Household Lifecycle Theory (Perz and Walker, 2002; Walker et al., 2002); however, without more longitudinal data for our study this possibility is difficult to verify.

In contrast to the significant differences observed for stepping-out and subsistence households, it is notable that there was less variation in household characteristics among the other household types (**Table 5**). This suggests that between the higher and lower ends of the spectrum for household characteristics, livelihood diversification may be being driven by the influence of other factors. As concluded by a study in the Andean valleys of Bolivia, structural factors are also likely to be highly influential in terms of which pathways farming households employ as livelihood strategies (le Grand and Zoomers, 2017). Indeed, as argued by Black et al. (2011), environmental, political, demographic, social, and economic factors are all likely to mediate household level decisions with regard to how and whether to incorporate off-farm income opportunities presented by enhanced rural mobility into livelihood strategies.

In the current study these structural effects on livelihood diversification may be borne out in a number of ways. For example, the Ecuadorian research site was characterized by the highest proportion of households with a stepping-out livelihood strategy (**Table 2**), despite the households in this country's survey registering older heads of household on average (54.1 years compared to 48.1 and 48.6 in Peru and Bolivia, respectively). Part of the reason for this finding may be related to the fact that the Ecuadorian rural households may have had better access to off-farm employment, as transport links and distances to economic centers was relatively favorable compared to the other countries. On the other hand, in Peru there were proportionally fewer commercial farm households and more subsistence households. This could have been a result of the fact that the location of the research site results in more households that were at very high elevations with significant challenges in terms of access to markets and irrigation water. Finally, in Bolivia, very few households were observed to incorporate off-farm income generating activities within their livelihood strategies. Indeed, no household in Bolivia was observed to be "stepping-out" of farming. Part of the reason for this is likely due to the fact that farming in the communities in Bolivia from this study was much more profitable than farming in the communities from Ecuador or Peru. According to our data, on average farming households from Bolivia generated over twice as much income from farm production ($3,000) than Ecuador ($1,190), and over four-fold more than Peru ($692).

As such, our findings suggest that while household level characteristics may have an important role to play in influencing the livelihood strategies households employ, these variables should not be perceived as deterministic, such that "younger" households will always employ commercial or stepping-out livelihood strategies. Instead, we argue that the potential influences of different household characteristics on livelihood strategies will also vary from location to location and household to household. This conclusion reflects other studies who have found important location-specific influences on the incorporation of rural mobility opportunities within the overall livelihood strategies of households (de Sherbinin et al., 2008; Radel et al., 2019). For example, in a study from Ethiopia, while a number of different household characteristics, such as age and education of household heads, were observed to have important influences on whether members of a household would incorporate off-farm income activities within their livelihood strategies, location was also a strong determinant (Tegegne and Penker, 2016).

Further research is recommended to explore how different household characteristics may be interrelated, how these patterns may change over a farming household lifecycle, as well as their relationship with other macro-scale variables, in order to build a better appreciation of the pathways which influence the adoption of different livelihoods and to guide future and more nuanced intervention strategies.

Policy Implications

Our findings suggest that rural development programmes and projects need to explicitly recognize this diversity in household livelihood strategies for more effective engagement and innovations with rural farming communities. For example, interventions aimed at commercial farm or mixed livelihood households are unlikely to be effective for subsistence or stepping-out livelihood strategy households. Not only are farming priorities likely to be different, but inherent opportunities for and barriers to more sustainable change are likely to differ for the different household types, and by context and location (Ruben and Pender, 2004). As we have seen in the results from this study and others, while the generation of high-value off farm income may be an option for livelihood diversification and therefore resilience-building for the younger more educated rural households, this may not be an option for other rural households. Without more nuanced approaches to development, that integrate these differences, rural development programmes, and policy is unlikely to be any more successful in the future (Descheemaeker et al., 2016). A concrete example of how this may be done was recently trialed in a project in Rwanda, where the use of household typologies enabled the characterization of the different populations into discrete groups in order to prioritize farm types for engagement, and locations for further investment (Hammond et al., 2020).

Moreover, given the large proportion of mixed livelihoods and commercial farms in the Andean communities studied here and their greater reliance on farming techniques that are associated with land degradation, such as the use of agrochemicals and mechanized tillage (Fonte et al., 2012), these groups of farming households could be viewed as high-leverage "audiences." Engagement with these household types on more sustainable agroecological intensification techniques is critical to transform overall landscape level agroecosystem performance. This is only likely achievable through a better understanding of their context and motivators. The fact that large proportions of households still practiced agroecological techniques (**Table 6**), even within farming households that employed more industrialized approaches to farming, indicates a promising entry point for engagement on agroecological intensification. To this extent it will be important to engage in the already lively debate in these rural communities around the desirability of agroecological and industrialized approaches to farming, recognizing that choices are driven by local norms and conversations.

CONCLUSION

Household livelihood strategies that incorporate off-farm income through the opportunities presented by rural mobility are associated with different approaches to farm management. Our findings suggest that this relationship does not boil down to a direct linear relationship between off-farm diversification and farm management. Instead enhanced rural mobility and access to off-farm income opportunities appears to facilitate greater livelihood diversification with intricate links with farm management approaches enabling rural households to "remain." Another important finding in this study is that household characteristics played an important role in influencing rural households' livelihood strategy. Age and education, in particular, appear to be variables that influence the ability of households to integrate higher value off-farm income activities into their livelihoods. However, we argue that these variables should not be perceived as deterministic. Indeed, despite similar household characteristics a number of livelihood strategy types exhibited important differences in their approach to farm production and management. In these cases, other, location-specific, contextual factors are likely to be highly influential in terms of which pathways farming household choose as livelihood strategies. From a policy perspective this research provides important insights for improved rural development. In particular, the relationships between household characteristics, livelihood strategies and farm management underline the argument that drivers for more or less sustainable land management will vary location to location and household to household. Programmes and projects must therefore take into account this heterogeneity and engage in the already advanced conversations around different approaches to farming and the conservation of common natural resources.

TABLE 6 | Estimated marginal means for farm management practices of the different household livelihood strategy types[#].

Farming management/technique		Livelihood strategy type						
		FF1—LS specialists	**FF2—commercial farms**	**FF3—crop specialists**	**FF4—subsistence**	**OF1—mixed livelihoods**	**OF2—mixed LS specialists**	**OF3—stepping-out**
Industrialized farming techniques	Mechanized tillage	0.49 (0.12)b	0.60 (0.15)b	0.46 (0.13)b	0.20 (0.09)a	0.53 (0.13)b	0.28 (0.13)ab	0.27 (0.12)ab
	N fertilizer inputs	2.58 (0.87)c	2.44 (1.32)c	2.11 (0.83)c	0.33 (0.19)a	4.07 (1.56)c	1.36 (0.77)bc	0.40 (0.24)ab
	Pesticides	0.58 (0.09)bc	0.87 (0.06)d	0.59 (0.10)bc	0.47 (0.11)ab	0.71 (0.08)c	0.42 (0.12)ab	0.33 (0.10)a
Agroecological farming techniques	Agroforestry	0.63 (0.07)ab	0.81 (0.09)b	0.61 (0.08)ab	0.55 (0.1)a	0.63 (0.09)ab	0.66 (0.1)ab	0.71 (0.09)ab
	Manure inputs	0.62 (0.15)bc	0.38 (0.17)a	0.58 (0.16)abc	0.72 (0.14)c	0.62 (0.16)abc	0.44 (0.18)ab	0.70 (0.15)bc
	Crop rotation	0.89 (0.18)a	0.86 (0.23)a	0.82 (0.28)a	0.90 (0.17)ab	0.89 (0.18)ab	0.95 (0.08)b	0.91 (0.15)ab
	Use legumes	0.89 (0.18)a	0.86 (0.23)a	0.82 (0.28)a	0.90 (0.17)ab	0.89 (0.18)ab	0.95 (0.08)b	0.91 (0.15)ab
Crop and livestock diversity	Crop diversity	2.84 (0.17)b	2.91 (0.23)b	2.88 (0.19)b	2.38 (0.18)a	3.01 (0.2)b	2.78 (0.24)ab	2.68 (0.23)ab
	Livestock diversity	2.25 (0.13)abc	2.4 (0.16)bc	2.06 (0.15)a	2.03 (0.17)a	2.24 (0.14)abc	2.42 (0.17)c	2.06 (0.18)ab

*Standard errors are presented in parentheses and results from Fisher's least significant difference test are indicated by lower case letters next to standard errors, such that livelihoods with different letters have different estimated marginal means at the 5% significance level. See **Table 1** for description of variables and units.*

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

MC performed the statistical analysis and wrote the first draft of the manuscript. All authors contributed to conception and design of the study, data collection, manuscript revision, read, and approved the submitted version.

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SUPPLEMENTARY MATERIAL

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A Living Income for Cocoa Producers in Côte d'Ivoire and Ghana?

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It is often claimed that cocoa producers are poor, but the extent of their poverty is rarely defined. We analyzed six data sets derived from household questionnaires of 385–88,896 cocoa producers in Côte d'Ivoire and Ghana. Across all data sets, many households (30–58%) earn a gross income below the World Bank extreme poverty line and the majority (73–90%) do not earn a Living Income. Households with less income per person per day generally achieve lower cocoa yields, consist of more household members, have a smaller land size available, and rely more on cocoa income than households with higher incomes. When comparing the effects of increasing prices and yields on gross income, yield increases lead to larger benefits especially for the poorest households. Doubling the cocoa price would leave 15–25% of households with a gross income below the extreme poverty line and 53–65% below the Living Income benchmark. At yields of 600 kg/ha, against current yields around 300 kg/ha, these percentages are reduced to 7–11 and 48–62%, respectively, while at yields of 1,500 kg/ha only 1–2% of households remain below the extreme poverty line and 13–20% below the Living Income benchmark. If we assume that the production costs of achieving a yield of 1,500 kg/ha are 30% of revenue, still only 2–4% of households earn a net income below the extreme poverty line and 25–32% below the Living Income benchmark. Whilst sustainable intensification of cocoa production is undoubtedly a strong approach to increase cocoa yields and farmer incomes, achieving this does not come without pitfalls. The poorer households face multiple barriers to invest in cocoa production. A better understanding of cocoa producing households and the resources available to them, as well as the opportunity for alternative income generation, is required to tailor options to increase their income. The utility and interpretability of future household surveys would be drastically improved if definitions and variables addressed were approached in a standardized way.

Keywords: smallholder farms, poverty benchmarks, sustainable intensification, household surveys, cocoa production

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INTRODUCTION

Most of the world's cocoa originates from West Africa, with Côte d'Ivoire and Ghana contributing more than 60% of all cocoa (ICCO, 2019). Virtually all cocoa in West Africa is produced by smallholder farmers, many of whom are poor (e.g., Fountain and Hütz-Adams, 2018; Cargill, 2019; Fairtrade, 2020). Both Côte d'Ivoire and Ghana have taken a variety of measures to make cocoa more profitable for farmers, through the Conseil du Café-Cacao and the Ghana Cocoa Board (Cocobod), respectively.

In the early 2000s, Ghana offered farmers improved varieties, subsidized fertilizer and free pest and disease control, set a pan-territorial producer price, and simultaneously increased farmers share in cocoa export prices. In a context of high world market prices these measures resulted in increased productivity and a drop in poverty levels between 1990 and 2005 (Vigneri and Kolavalli, 2018). In Côte d'Ivoire the government also fixed cocoa prices relative to the international market to assure farmers a stable income with positive effects between 1979 and 1999 (Coulibaly and Erbao, 2019), but invested little in input supply. With time cocoa could no longer benefit from the natural fertility of soils on which it was planted (the so-called "forest rent" Ruf and Schroth, 2004). As a consequence productivity declined, and since 2000 as costs of production increased farmers became poorer both in Côte d'Ivoire and Ghana (Odijie, 2016). In 2014, 10 of the largest chocolate multinationals introduced a cocoa sustainability scheme called CocoaAction, jointly investing 500 million USD in sustainable cocoa production in West Africa to support cocoa planters and counteract these trends, out of fear of insufficient supply of cocoa beans (Odijie, 2018). In 2019, the governments of Côte d'Ivoire and Ghana introduced a premium on the export price of cocoa for the 2020/2021 season, known as the Living Income Differential, of USD 400 per ton. The question is whether all these efforts have allowed cocoa farmers to reach a living income nowadays.

Many local and international organizations, together with companies involved in the procurement or processing of cocoa, have committed to ensure increased incomes of cocoa producers in their supply chains. For instance, Barry Callebaut in their "Forever Chocolate" have resolved to lift more than half a million cocoa farmers out of poverty by 2025 (Barry Callebaut, 2018). Cargill mentions that "Many farmers struggle to achieve a Living Income and as a result face being trapped in a cycle of poverty" and suggests ways in which they help farmers increase their income through the Cocoa Promise programme (Cargill, 2019). Net income from cocoa and from other sources are among the key performance indicators of the Cocoa Life Programme (Mondelēz International, 2020). A focal area of the "Cocoa for Generations" programme is to improve farmers' incomes (Mars, 2020).

The involvement of confectionary companies in issues of poverty and labor rights has a rich tradition. Two famous chocolatiers, the Rowntree and Cadbury families, were Quaker industrial philanthropists who cared for their workers. Seebohm Rowntree was the first to use a "cost of basic needs" approach to derive a poverty line for workers at the end of the nineteenth century (Rowntree, 1901; Ravallion, 2000, 2008). It is less clear whether these companies ever considered the farmers and farm workers who produced the cocoa they used to make chocolate in their factories, as is the focus today.

Today, many trading and confectionary companies as well as other organizations such as Solidaridad, FairTrade, and CocoaBarometer report on statistics such as current average cocoa farmer incomes or the proportion of producers who live in poverty. However, the metrics they present vary. First, different benchmarks to define poverty are used. Second, the methods used to calculate the income of cocoa producers differ. Poverty is measured against different standards. In 1990, the World Bank introduced the concept of the "global poverty line" to allow for cross-country comparison and aggregation, based on national poverty lines for a number of lowest income countries at that time (World Bank, 1990). Based on this report, the "1 dollar a day" standard to measure extreme poverty, which was expressed in Purchasing Power Parity (PPP) 1985, became accepted by the World Bank and internationally (World Bank, 1990; Ravallion et al., 2009). Purchasing Power Parity is a way to convert monetary values to a theoretical common currency, taking into account the relative cost of living and inflation rates in different countries. Based on a larger set of national poverty lines and new PPP conversion factors, the 1 $ a day threshold was revised to 1.25 $ (PPP 2005) per capita per day in 2009 (Ravallion et al., 2009), and again to 1.90 $ (PPP 2011) per capita per day in 2015 (Ferreira et al., 2016). This is the current global extreme poverty line. Indeed, Barry Callebaut is using this poverty line as a benchmark for their ambition to lift half a million farmers out of poverty by 2025 (Barry Callebaut, 2021).

Recently, the concept of "Living Income" has gained attention as an income benchmark, especially in the context of export commodities such as cocoa (e.g., Fountain and Hütz-Adams, 2015, 2018; Fairtrade, 2018; Tony's Chocolonely, 2018; Cargill, 2019). The Living Income Community of Practice, defines Living Income as: "*The net annual income required for a household in a particular place to afford a decent standard of living for all members of that household. Elements of a decent standard of living include: food, water, housing, education, healthcare, transport, clothing, and other essential needs including provision for unexpected events*" (Living Income Community of Practice, 2020). A Living Income thus addresses the basic human rights to food, shelter, housing, and education (Van De Ven et al., 2020). The Living Income benchmark for a specific country or region generally lies above the national or global poverty lines, as more items are considered to be required for a decent standard of living than what is usually included in the "consumption basket" used to calculate the poverty lines (Van De Ven et al., 2020).

There is a rich literature on the role of agricultural production in smallholder livelihoods (e.g., Boserup, 1965; Ellis, 1993), that remains largely unexplored in the case of cocoa producers. Of particular importance, is the recognition that smallholders often depend on a diverse range of income streams, both on and off the farm (Ellis, 1998; Ellis and Freeman, 2004). The most recent and comprehensive study of cocoa production to date in West Africa is that conducted by the Royal Tropical Institute (KIT) (Bymolt et al., 2018). Based on our reading of the literature, we summarize our understanding of the relationships among variables that determine the income of cocoa producing households in **Figure 1**. Cocoa is key to the livelihoods of smallholder cocoa producers in both Côte d'Ivoire and Ghana, representing roughly two-thirds of income in both countries (Bymolt et al., 2018), so the farm area cropped with cocoa, the cocoa yield, and the price farmers receive for their cocoa all have a large effect on total household income.

There is potentially a self-amplifying mechanism between household income, input use, and cocoa yield (**Figure 1**) which is positive for wealthier households. Unfortunately, the same

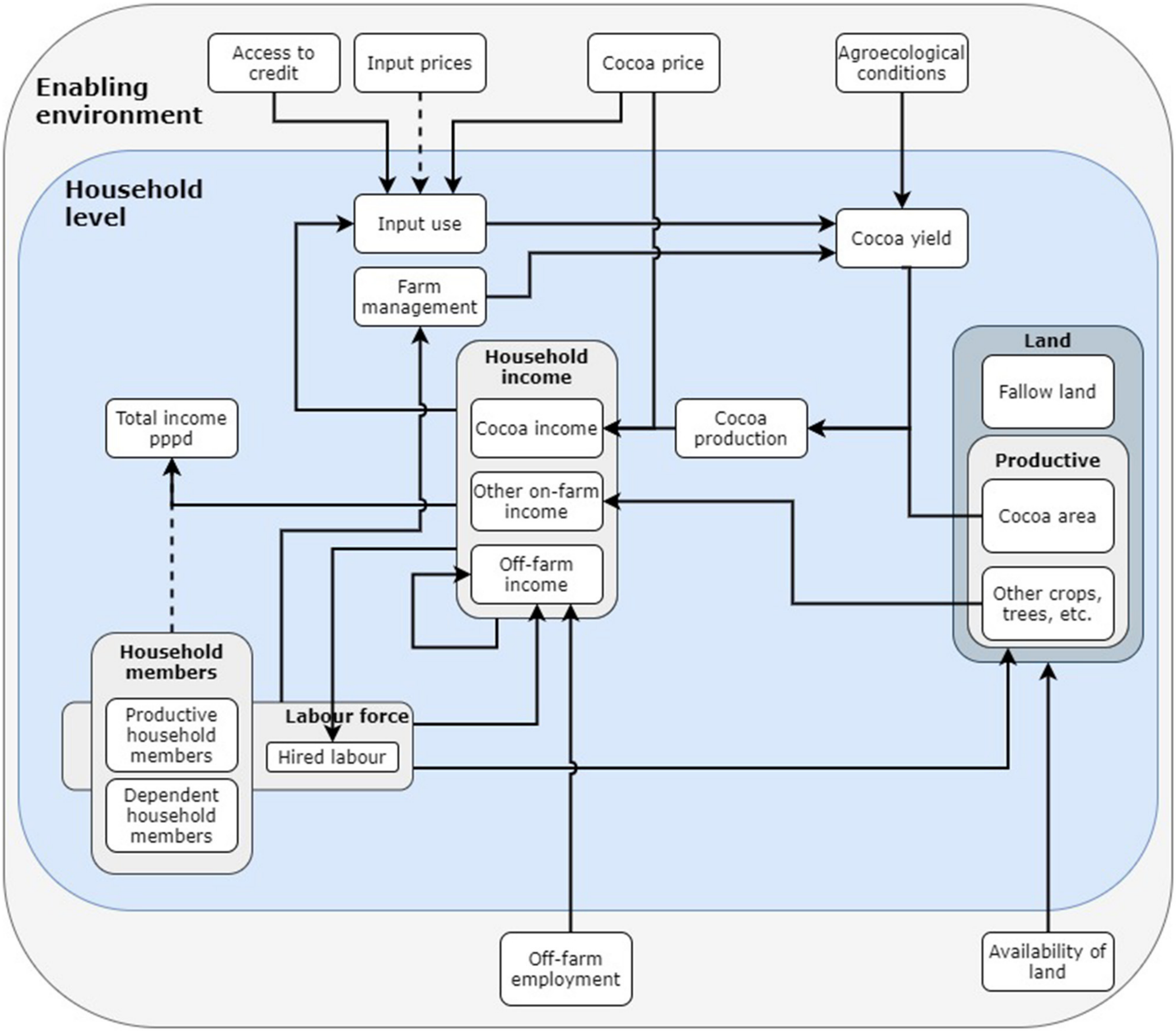

FIGURE 1 | Conceptual causal diagram of important variables related to the income of cocoa producing households. Dashed arrows represent negative effects, continuous arrows positive effects.

mechanism can bring poorer farmers into a negative spiral or poverty trap where their cocoa area and yield is too small to earn a decent income from cocoa, while their lack of income prevents them from being able to invest in inputs to improve their yield. Similarly, households with a higher income are more likely to be able to afford to hire labor, giving them access to a larger labor force, and therefore a higher income (**Figure 1**). Availability of land, labor, and capital also gives more opportunities to earn income from other sources than cocoa. A small total income can be both a cause and a consequence of a lack of alternative sources of income because often some form of capital is required to engage in more lucrative income generating activities (Alobo Loison, 2015). On the other hand, when income from cocoa is high, there is less need for other sources of income to earn a high total household income. Unfortunately, the calculation of income of smallholder cocoa producers, and of their dependence on different income streams, is not straightforward. No formal pay checks are available, income is often generated by several household members and may come from many different on and off-farm sources, and some income is received in-kind, for instance in the form of food, rather than money (Tyszler et al., 2018c).

Cocoa yields on smallholder farms in West Africa remain stagnant around 400 kg/ha/yr (Van Vliet and Giller, 2017). Theoretical studies suggest the crop could produce 10 times as much under the West African climate if all nutrient constraints were removed and pests and diseases controlled (Zuidema et al., 2005). Given the importance of cocoa to smallholder livelihoods, its continued poor productivity also represents a poverty trap (cf. Tittonell and Giller, 2013), emphasizing the need to increase cocoa yields. Vanlauwe et al. (2014) highlight the need to enhance agricultural productivity in sub-Saharan Africa through sustainable intensification, buffering farmers against shocks and paying attention to restricting expansion of the area under agriculture to maintain other ecosystem services. Sustainable intensification of smallholder cocoa production through optimizing management practices is certainly feasible: yields of up to 3,000 kg/ha have been reported on some smallholders' farms in Ghana, with an average yield of about 1,225 kg/ha (Mondelēz International, 2019). Aneani and Ofori-Frimpong (2013) estimate that on-farm yields of 1,875 kg/ha are plausible in Ghana based on the maximum farmers' yields found in a previous study, and Abdulai et al. (2020) recorded farmers' yields of 2,125 kg/ha.

Despite the widespread attention, information on the current status of poverty and the income of smallholder cocoa producers remains limited to a small number of sources. In this article we address two main questions. First, we assembled all the different datasets from household surveys we could access, and used them to calculate the income of cocoa producing households in Ghana and Côte d'Ivoire, to address the question as to whether they would lead to similar conclusions to be drawn on the incidence of poverty and income. We compare these incomes with the World Bank extreme poverty line and the Living Income benchmarks of both countries. To understand the differences between the outcomes, we investigated the variables underlying income per person per day such as household size, cocoa yield, farm size, and income from sources other than cocoa.

Second, increases in yield (e.g., World Cocoa Foundation, 2017; Cargill, 2019; Mondelēz International, 2019) and/or increases in cocoa prices received by producers (e.g., Fountain and Hütz-Adams, 2018; Solidaridad, 2020a; Tony's Chocolonely, 2020) are frequently proposed as options to improve the income of cocoa producing households. Given our interest in the sustainable intensification of cocoa production, we used the most comprehensive dataset available to explore the question as to what are the relative impacts of raising the price that farmers are paid for their cocoa compared with the effect of increasing cocoa yields on the incidence of poverty and income.

METHODS

Datasets Used

Several data sets from household surveys concerning smallholder cocoa production in Côte d'Ivoire and Ghana were compared (**Table 1**). The household surveys were conducted for different reasons using different questionnaires and different sampling strategies.

In terms of data cleaning, apart from cocoa yields we did not set any definition of "outliers." Although some values seemed unlikely we had no firm basis to exclude data as we were unable to check the validity of values with the interviewees. An exception is yield. Yields exceeding 2,000 kg/ha are rare, but possible. However, it is virtually impossible for cocoa yields in West Africa to exceed 5,000 kg/ha (Van Vliet and Giller, 2017). Hence, all data of variables related to yields above this threshold were excluded (i.e., yield, cocoa land size, cocoa production, and income). This was only the case in the Cargill data set, and applied to <0.1% of the respondents. In some data sets, zero values were excluded from the analyses because they seemed to represent missing data. In other data sets, the nature of the calculation of some variables led to exclusion of zero values. For consistency, zero values in variables regarding cocoa land and production were excluded from all data sets. This means that only producers which had (access to) cocoa land and cocoa production, and therefore cocoa income in the year of study, were included. Zero values of household size were also excluded. Outliers (defined as values deviating four standard deviations or more from the mean per country) for a number of numeric variables (e.g., land size, cocoa production, cocoa yield, number of household members) were removed from the KIT data set prior to publication of the data (Tyszler et al., 2018c). We used the data set from KIT for the analysis of relations between variables and for the scenarios, as this survey is the most complete, recent, and has the most random sample of cocoa producers of the different surveys available.

Variables explored were income, cocoa yield, cocoa area, and total farm area. Pearson correlation analyses were conducted to assess the relationship between total gross income per household member per day and several relevant variables. All calculations, analyses, and graphs were done using R 3.5 (R Core Team, 2018).

Gross and Net Income ($ PPP 2018 per Person per day)

Income was expressed in $ PPP 2018 per person per day (pppd). All income sources for each household were grouped into either "Cocoa income" (gross cocoa income, as it was not possible to calculate net income for all the data sets), "Other on-farm income" (income from other crops than cocoa, and livestock), and "Off-farm income" (all other sources of income, e.g., off farm employment). Income from sources other than cocoa were not available in the Cargill data set. Gross cocoa income was calculated based on total cocoa production of the household and the cocoa price of the year of data collection (**Table 2**) rather than using respondents' estimates of cocoa income.

For the KIT database, where more detailed information on expenditure was available, net income from cocoa was calculated. Income from other sources was based on respondents' estimates. Note that cocoa prices, expressed in $ PPP 2018, may differ by as much as a third between years, though this difference would have been much larger when comparing the cocoa prices in local currency without taking into account inflation and purchasing power per year and country. Household income was then divided by the number of household members and by 365 to arrive at gross income per person per day. Income in local currency (CFA or GH₵) was converted from its value in the year of collection to its value in 2018 using Consumer Price Indices (World Bank, 2019). Finally, all income data was converted from local currency (2018) to $ PPP 2018 using PPP conversion factors (World Bank, 2019).

TABLE 1 | Data sets of cocoa-producing households surveyed in Côte d'Ivoire (CDI) and Ghana.

Data set	Objective of the study		Geographic locations	Sampling method	For our research	Income	Land availability	Household members	Yield
KIT	To conduct a major household study in cocoa growing regions to better understand the relative importance of cocoa in comparison to other crops, the livelihood status of different households, and intra-household dynamics and make these data freely available	Ghana	Regions: Ashanti, Central, Brong Ahafo, Western, and Eastern	Random selection of communities. Households selected using transect walks in four directions per village, all households were eligible. Minimum one third female selected. Respondents do not need to be household head	Only households that produced and sold cocoa were selected	Study calculates gross cocoa income by multiplying total number of bags produced per household per year with fixed price. We recalculated total cocoa production in kg for Ghana using a weight per bag of 62.5 kg rather than 64 kg.	Study provided data on land used for cocoa, all cultivated land and all fallow land. We calculated total land (cultivated + fallow) and land for other crops (cultivated-cocoa land).	Household consists of all members that live in the main compound/house and usually eat together	Yield is total production divided over total area per household Mean ± SD threshold to remove outliers.
		CDI	Districts: Autonome de Yamoussoukro, Lacs, Montagnes, Bas-Sassandra, Goh-Djiboua, Zanzan, Sassandra-Marahoue, Comoe, and Lagunes						
WUR	To conduct a baseline assessment of six cocoa projects within a cocoa programme implemented in Ghana, Commissioned by UTZ, Solidaridad and IDH	Ghana	Regions: Ashanti, Eastern, and Western	Random selection of producers from six project groups working toward certification and for comparison from three communities that did not receive any training related to certification and were 10 km away from project assisted communities. Farmers were later stratified in different stages of certification	We did not distinguish between the project and comparison groups	We calculated gross income from cocoa by multiplying cocoa production as number of bags from the three main plots per farm times 62.5 kg/bag times the cocoa price of 2010/11. Only 12% of farmers have more than three cocoa plots. Data on other income were used as reported.	Only data on number of plots and sizes of the three largest plots. No data on other land use.	idem.	idem but for the three largest plots per household.

(Continued)

TABLE 1 | Continued

Data set	Objective of the study		Geographic locations	Sampling method	For our research	Income	Land availability	Household members	Yield
WUR	To conduct a baseline assessment of cocoa projects within a cocoa programme implemented in Cote D'Ivoire, Commisioned by UTZ, Solidaridad and IDH	CDI	Districts: Lacs, Montagnes, Bas-Sassandra, Gôh-Djiboua, Sassandra-Marahoué, Comoé, Lagunes	A stratified sample of farmers was selected, aiming to be representative of UTZ programme cocoa farmers in terms of membership of coops with and without linkages to traders, coops at different stages of certifications and training, coops located in three different agro-ecological zones, and farmers not in the UTZ programme (comparison group).	We used the full data set without distinguishing the various groups.	Gross income from all plots based on production and price. Data on other income were used as reported.	Number and size of all cocoa plots per household available. Used to calculate total coca cultivated area	idem.	idem
Cargill	To measure progress, performance, and cocoa production of the farmers as the core of the monitoring and evaluation system of Cargill	CDI	Autonome de Yamoussoukro, Lacs, Montagnes, Bas-Sassandra, Goh-Djiboua, Zanzan, Sassandra-Marahoue, Comoe, and Lagunes.	Farm and household data collected by coaches and cocoa production data collected by cooperatives were received for all members from UTZ certified cooperatives that all received personal coaching. Only 5% of the farmers in the dataset were not yet certified.	We merged the datasets and used the data of all farmers for the years 2017–2018	Gross cocoa income based on production multiplied by price of 2017/18 plus premium of 35 CFA/kg	Data on cocoa cultivated land, forest and fallow but not on other crops. Total area per household could not be calculated.	Number of people reported to be under the care of the cocoa farmer plus one (respondent).	idem
Ghent Univ. /Univ. of Ghana	To analyse the determinants of cocoa productivity and profitability by smallholder farmers in Ghana to provide insights into challenges for future cocoa farming, to guide the formulation and prioritization of tailored policies to address them	Ghana	Regions: Ashanti, Brong Ahafo, Central, Eastern, Volta, and Western	In each region, five cocoa growing districts were randomly selected except for Central (all 4) and Volta (all 2). In each district two communities were randomly selected from which cocoa producer were selected by extension workers.	We used all available data	Cocoa production was recalculated using a weight per bag of 62.5 kg rather than 64 kg. Gross cocoa income calculated by multiplying kg produced with a fixed price. Data on total gross income were used as reported	Number and size of each cocoa field were reported from which we calculated total cocoa cultivated land per household. Study provided no information on other land uses.	Total household size was the sum of number of husbands or wives, sons and daughters and other dependents plus one (respondent)	Yield calculated as cocoa production for year 2013/14 divided by cocoa area per household

TABLE 2 | Standardization of cocoa prices per kg to $ purchasing power parity ($ PPP 2018).

Study	Country	Data year	Local currency[a] in data year	Local currency calculated to 2018	$ PPP 2018
WUR	Ghana	2011/2012	3.20	7.51	4.53
WUR	Côte d'Ivoire	2011/2012	725	770	3.39
Ghent University	Ghana	2013/2014	3.39	5.76	3.48
KIT	Côte d'Ivoire	2015/2016	1000	1011	4.45
KIT	Ghana	2015/2016	6.80	8.39	5.07
Cargill	Côte d'Ivoire	2017/2018	735[b]	735	3.23

Conversions were made from local currency in the year of data collection (for a crop year spanning two calendar years we used the second year) to 2018 and to $ PPP 2018 based on World Bank (2019) conversion factors.
[a]GH₵ for Ghana and CFA for Côte d'Ivoire.
[b]This includes a cash premium of 35 CFA/kg of cocoa.

Cocoa Yield

Average yields (kg of fermented dry beans) per household were calculated as total household cocoa production divided by total area of cocoa per household. This included area which had been (re)planted recently and was not yet in production, which may be up to 24% of the land under cocoa (based on the KIT data for Ghana). The yield of the total cocoa area is thus an underestimation of the yield on productive cocoa land. Note that the cocoa area may include land which is cropped but not owned by the respondent.

Income Benchmarks

We compared the calculated incomes per person per day against two benchmarks: the World Bank international extreme poverty line and the Living Income benchmarks of Ghana and Côte d'Ivoire according to the Living Income Community of Practice. The World Bank international extreme poverty line is set at 1.90 $ PPP (2011) per person per day (Ferreira et al., 2016), which equals 2.12 $ PPP (2018) (World Bank, 2019). Since 2017, the World Bank also reports a poverty line of 3.20 $ (PPP 2011) per capita per day for lower-middle-income countries such as Ghana and Côte d'Ivoire besides the extreme poverty line (World Bank, 2018). Nevertheless, we use the 1.90 $ (PPP 2011; which is 2.12 $ PPP 2018) line as this remains the most widely used as an income benchmark (e.g., Barry Callebaut, 2018).

The Living Income benchmark for Ghana was established by Smith and Sarpong (2018) for rural cocoa producing areas in Ashanti, Central, Eastern, and Western Regions. It was set at GH₵1,464 per month for a typical reference family of two adults and three children. We recalculated this to GH₵ per person (divide by 5) per day (multiply by 12 months, divide by 365 days). Then we recalculated to $ PPP (2018) using the GH₵-PPP conversion factor for 2018 (World Bank, 2019). This comes to 5.81 $ PPP (2018) per person per day. The Living Income benchmark for Côte d'Ivoire was established by CIRES (2018) for rural cocoa growing areas. It was set at CFA 262,056 per month for a typical reference family of two adults and four children. This was recalculated as described above for Ghana to give 6.32 $ PPP (2018) per person per day. As the annual Living Income benchmark is often calculated on the basis of a typical reference household, we converted to per person per day using the number of household members of the reference household to allow comparison of households of different size. Tyszler et al. (2018a,b) chose to differentiate by using three contrasting reference households to establish different Living Income benchmarks and then compared each household to the most similar reference household. Van De Ven et al. (2020) recommend standardization of incomes using equivalence scales to account for the varying needs of household members in terms of food and income. Insufficient information was available from all of the surveys to allow this, but we conducted an exercise with the KIT data to explore the effect of using the adult equivalent (AE) for income (see **Supplementary Figure 1**).

Scenarios

We explored the effect of increasing the price paid to farmers for their cocoa and the effect of increasing cocoa yield on the proportion of cocoa producers who fall below the poverty line of the Living Income threshold, using the KIT survey data. Increasing cocoa price and increasing cocoa yield are the two most often mentioned options to increase income.

The effect of increasing the price was explored in two ways: first by imposing the Living Income Differential of 400 USD per ton recently agreed by the governments of Côte d'Ivoire and Ghana (Reuters, 2019); and second by doubling the cocoa price compared to that of 2015/2016. The first was based on the conversion of the minimum farm gate price for 2020/2021 resulting from the Living Income Differential (1,820 USD/ton) to local currency and then to PPP 2018, which comes to cocoa farm gate prices of 5.04 $ PPP/kg in Ghana and 4.45 $ PPP/kg in Côte d'Ivoire. The latter is close to the minimum price proposed by Fountain and Hütz-Adams (2019) following a similar method of calculation, which according to them is required for cocoa producers to earn a Living Income.

The effect of increasing cocoa yield was explored by increasing yields of all households to 1,500 kg/ha. Although few producers currently achieve such yields, it is certainly possible to reach 1,500 kg/ha or more on farmers' fields using what can be considered to be best management practices (i.e., pruning, crop protection methods, and fertilizer use) (Aneani and Ofori-Frimpong, 2013; Mondelēz International, 2019; Abdulai et al., 2020). Additionally, we tested the effects of increasing farmers' cocoa yields more modestly to 600, 800 and 1,000 kg/ha. In the scenarios, we assumed no change in non-cocoa income. Increased investment in inputs (of labor, fertilizer, and plant protection agents) is needed to increase yields. We therefore tested the effect of increasing yields to 1,500 kg/ha while subtracting 30% of the cocoa income as the investment costs (inputs plus labor) required to boost production, which is a generous allowance compared with what farmers invest currently in inputs and labor (Smith and Sarpong, 2018).

RESULTS

Differences in Household Income Among the Surveys

The incomes of many cocoa producing households in both Ghana and Côte d'Ivoire fell below the World Bank extreme poverty line of 2.12 $ (PPP 2018), and the majority were below the Living Income benchmark of 5.81 $ (PPP 2018) for Ghana and 6.32 $ (PPP2018) for Côte d' Ivoire (**Figure 2**). There were also households whose income was well-above the Living Income benchmark, but these were rare in all data sets.

Although the overall patterns found are the same with all data sets, there were notable differences among countries and data sets (**Table 3**). The number of reported household members was larger in Côte d'Ivoire than in Ghana, and largest in the WUR study of Côte d'Ivoire. Although cocoa land area was generally somewhat smaller in Ghana, this area was divided over a larger number of plots than in Côte d'Ivoire. Mean and median yields were especially high in the Cargill study (Côte d'Ivoire) and lowest in the study of Ghent University (Ghana). Despite the low cocoa price (**Table 2)** and the relatively small cocoa land area, this leads to the highest mean and median income from cocoa per household member per day (pppd) in the Cargill study. The lowest mean and median income from cocoa pppd was obtained in the study of Ghent University. Mean and median total income pppd (not available for the Cargill study) was highest in the KIT study of Ghana. This was the consequence of high mean and median cocoa income pppd due to a high cocoa price (**Table 2**) and yields in combination with a larger amount of income from other sources. The lowest mean and median total income pppd was found in the WUR study of Ghana, resulting from a low cocoa income due to low yields and little income from other sources. In both countries, mean and median income from other sources pppd was highest for the KIT studies and lowest for the WUR studies. For further details see **Table 1**.

Relationships Between Income and Other Variables

The relationships between gross total income per person per day and a number of other variables were explored using the data from KIT (**Figure 3**).

There was a significant negative correlation between number of household members and income pppd (**Figures 3A,B**). The relation was stronger in Ghana ($r = -0.36$, $p < 0.01$), where of the households with income below the extreme poverty line, 73% had a household size larger than the population mean. This is 43% of those above the extreme poverty line. In Côte d'Ivoire, the relation was weaker ($r = -0.22$, $p < 0.01$) and of the households whose income was below the extreme poverty line, 56% were larger than the population mean while this was 39% for those above the extreme poverty line. On the other hand, the correlation between number of household members and total household income was positive, with a much stronger correlation in Côte d'Ivoire than in Ghana (**Supplementary Table 1**). In both countries, the spread of total income among more family members overrides the potential higher income earning capacity with more family members. There were relatively more dependents in larger families and a negative correlation between dependency ratio and income pppd (**Supplementary Tables 1**, **2**). There was a significant positive correlation between total available land (ha) and income pppd (**Figures 3C,D**). The relation was stronger in Ghana, where 79% of the households with income below the extreme poverty line had less land available than the population mean, while this was 56% of those above the extreme poverty line. In Côte d'Ivoire these percentages were 71% against 51%. When fallow land was excluded, the correlation remained almost the same in Ghana but was much stronger in Côte d'Ivoire (**Supplementary Table 1**).

There was a significant positive correlation between cocoa yield and income pppd (**Figures 3E,F**). More than 70% of the households which had an income pppd below the extreme poverty line had cocoa yields of <250 kg/ha in both countries, while only around 30% of the rest of the population had such poor yields.

There was a significant negative correlation between the proportion of income derived from cocoa sales, and income pppd (**Figures 3G,H**). The more dependent a household was on income from cocoa, the lower their total income pppd. In Côte d'Ivoire, of the households with an income below the extreme poverty line, more than 66% depended more on cocoa than the population mean, while this was 49% for those above the extreme poverty line. In Ghana this was 58% against 40%.

Note that the correlations of most variables with total household income are stronger than those with total income pppd (**Supplementary Table 1**) as income pppd is the combined result of total household income and number of household members. However, the income variable of interest is that per person, as household income does not reflect whether the needs of all household members can be met.

Exploring the Potential Effects of Increasing Cocoa Prices or Increasing Yields

We explored the impact of increasing the price paid to farmers for their cocoa in two ways. First, we changed the price paid to farmers according to the Living Income Differential for 2020/2021. In 2019, the governments of Côte d'Ivoire and Ghana applied a premium, known as the Living Income Differential, on the export price of cocoa for the 2020/2021 season of USD 400 per ton. This leads to a producer price increase compared with 2019/2020 of 1% in Ghana and 23% in Côte d'Ivoire, but virtually the same prices in $ PPP 2018 as in 2015/2016, and therefore virtually no effect on income per person per day compared with the baseline scenario (**Table 4**). Second, we doubled the cocoa

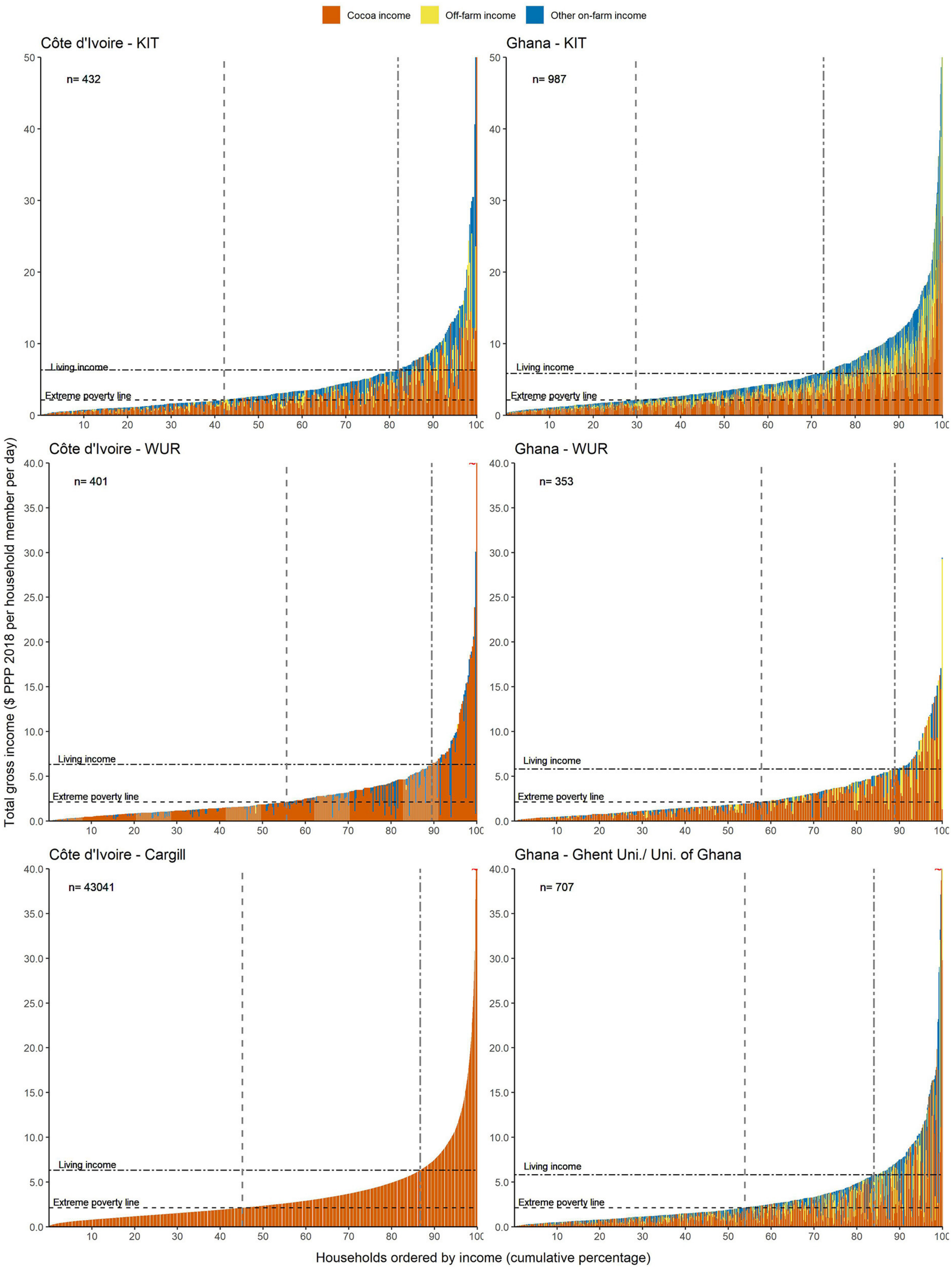

FIGURE 2 | Total gross income per household member per day ($ PPP 2018) for the six data sets, compared with the World Bank extreme poverty line and the Living Income benchmark in Ghana (based on Smith and Sarpong, 2018) and Côte d'Ivoire (based on CIRES, 2018). Note that only income from cocoa was recorded in the Cargill survey.

TABLE 3 | Summary of important variables calculated for each of the household survey data sets from Côte d'Ivoire and Ghana.

		Côte d'Ivoire			Ghana		
		Cargill	WUR	KIT	WUR	KIT	Ghent University
Number of observations used		88,896	426	992	385	1,384	731
Gender of the respondent (% male)[a]		94	97	73	81	67	77
Household members (#)	Mean	7.45	8.86[b]	6.99	6.04	5.86	6.46
	Median	7	8	6	6	6	6
	Range	1–51	1–30	1–21	1–18	1–16	1–18
Cocoa yield (kg/ha)[c]	Mean	587	435	295	275[d]	310	261
	Median	565	376	263	205	270	208
	Range	4–4,995	5–2,233	12–1,075	3–1,544	4–1,287	2–1,562
Cocoa land area (ha)	Mean	4.0	5.2	4.2	4.2	3.6	4.4
	Median	3.0	4.0	3.5	3.0	2.8	3.2
	Range	0.1–93.4	0.5–37.0	0.25–16.0	0.4–46.5	0.35–13.8	0.2–38.4
Total land area (ha)	Mean	n.a.	n.a.	9.0	n.a.	5.4	n.a.
	Median			7.5		4.25	
	Range			0.5–35.0		0.35–24.3	
Number of cocoa plots (#)	Mean	1.10	1.17	n.a.	2.16	n.a.	2.35
	Median	1	1		2		2
	Range	1–10	1–5		1–7		1–8
Gross cocoa income pppd (PPP 2018)	Mean	3.73	2.76	2.68	2.20[d]	3.10	2.13
	Median	2.34	1.55	1.61	1.40	2.02	1.07
	Range	0.04–167.88	0.01–58.83	0.04–60.96	0.03–16.30	0.02–34.71	0.02–44.67
Gross total income pppd (PPP 2018)	Mean	n.a.	3.19	4.48	2.86	5.44	3.43
	Median		1.86	2.67	1.81	3.47	1.90
	Range		0.01–58.83	0.04–76.20	0.03–29.42	0.05–69.42	0.05–45.44
Percentage income from cocoa (%)	Mean	n.a.	89	67	82	62	65
	Median		100	70	91	60	70
	Range		3–100	5–100	1–100	5–100	2–100
Poverty line (% of households below)		45	56	42	58	30	54
Living income benchmark (% of households below)		87	90	82	89	73	84

[a] *The respondents of the surveys were not necessarily the household heads.*
[b] *Number of household members was taken from the endline data set, as this survey used a more narrow definition of "household".*
[c] *Records with yields above 5,000 kg/ha were excluded.*
[d] *This is the area, yield and income of the three main plots of the farmer. Some farmers may have more than three plots.*

price compared with the prices of 2015/2016, which is virtually the same as doubling the price compared with that of 2019/2020 (**Figure 4**). In this case the percentage of households with gross incomes pppd below the extreme poverty line would be reduced from 42 to 25% in Côte d'Ivoire and from 30 to 15% in Ghana. The percentage of households with incomes below the Living Income benchmark would fall from 82 to 65% in Côte d'Ivoire and from 73 to 53% in Ghana.

We also explored the effect of increasing yields on gross income per household member (**Figure 5**). If producers would reach a cocoa yield of 1,500 kg/ha across their cocoa plantations, the percentage of households with incomes below the poverty line would be reduced from 42 to 2% in Côte d'Ivoire and from 30 to <1% in Ghana. The percentage of households with gross incomes below the Living Income benchmark would fall from 82 to 20% in Côte d'Ivoire and from 73 to 13% in Ghana. Cocoa farmers would need to invest more to achieve these increases in yields, yet if 30% of the increase in income was allocated to the input costs, the impacts on reducing the proportion of farmers below the poverty of Living Income benchmarks would also be strong (**Table 4**). If yields would increase more modestly the percentages of households with gross incomes below the poverty line are still reduced strongly compared with the baseline scenario or the scenarios where prices are increased (**Table 4**). The same holds true for households with gross incomes below the Living Income benchmark. When all else remains equal, yield increases thus have a larger effect on decreasing income gaps than price increases, especially for the poorest households.

DISCUSSION

Patterns of Poverty

Regardless of the survey methods used, the patterns of outcomes were similar (**Figure 2**). Overall, our findings converge to the conclusion that more than 40% of cocoa producing households in Côte d'Ivoire and 30% in Ghana fall below the World Bank

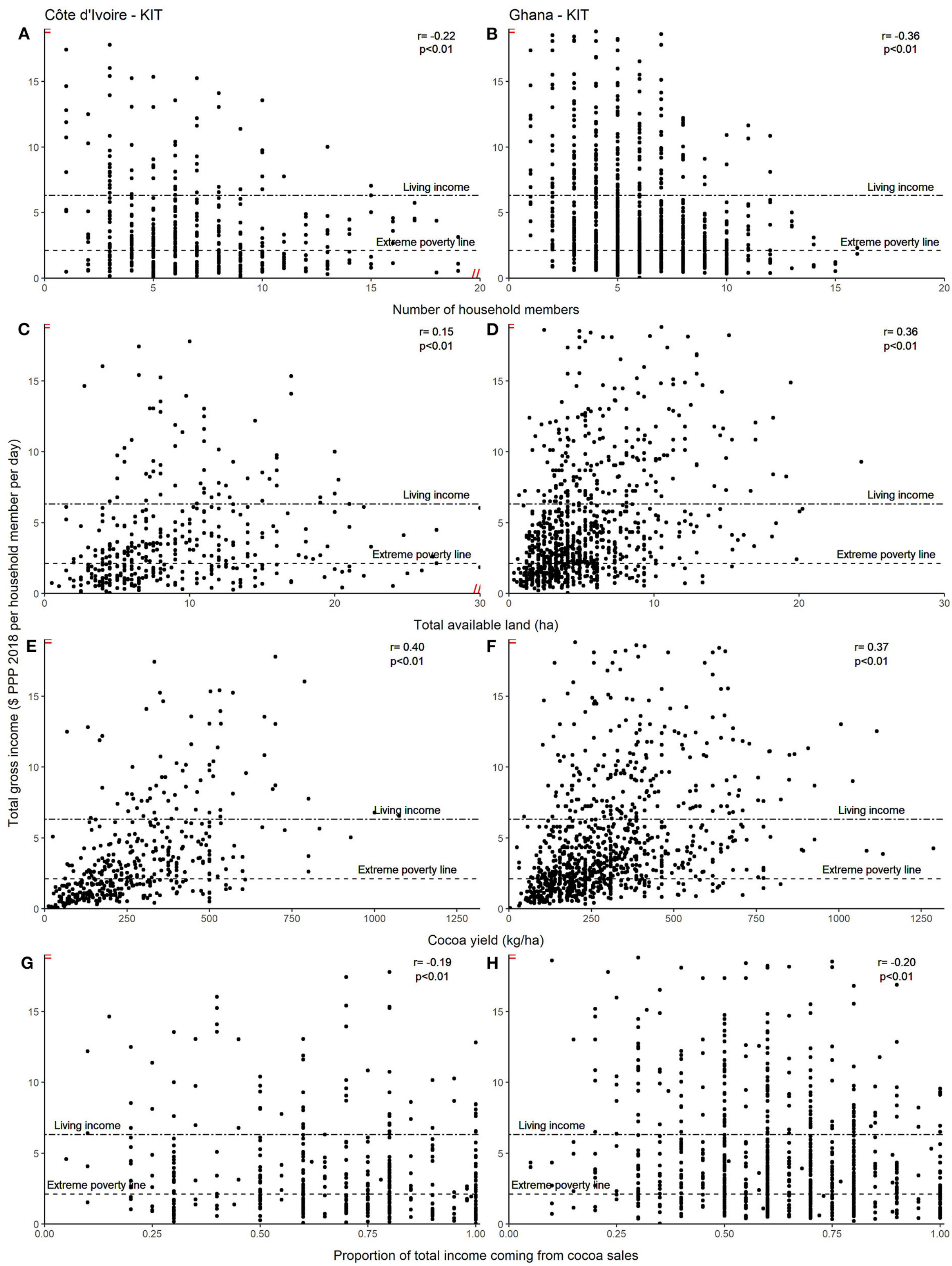

FIGURE 3 | Scatter plots of number of household members **(A,B)**, total available land (ha; **C,D**), cocoa yield (kg/ha; **E,F**), and proportion of total income coming from cocoa sales **(G,H)** over total gross income per household member per day based on data from KIT. r-values are Pearson correlations for each variable with income pppd.

TABLE 4 | Impacts of all scenarios related to increasing cocoa productivity or increasing the price farmers receive for their cocoa on the proportion of cocoa farmers who achieve an income equivalent to the World Bank extreme poverty line or the Living Income benchmark for Ghana of Smith and Sarpong (2018) and for Côte d'Ivoire of CIRES (2018).

	Ghana		Côte d'Ivoire	
	% of households with income below the			
Scenario	**Poverty line**	**Living income**	**Poverty line**	**Living income**
Baseline gross income	29.8	72.7	42.1	81.9
Baseline net income	32.0	73.3	44.3	82.5
Living Income Differential	29.9	72.7	42.1	81.9
Double cocoa price	14.8	52.6	25.0	65.0
Cocoa yield of 600 kg/ha	7.1	48.4	10.6	61.8
Cocoa yield of 800 kg/ha	3.3	35.4	8.6	46.3
Cocoa yield of 1,000 kg/ha	1.9	26.8	4.4	35.9
Cocoa yield of 1,500 kg/ha	0.6	13.3	1.6	20.1
Cocoa yield of 1,500 kg/ha, deducting 30% of cocoa income due to increased cost of production	1.6	24.5	3.5	31.9

All calculations were based on the KIT datasets and are based on gross household income except for the 'Baseline net income' scenario based on reported net income and the scenario where 30% of income are allowed for increased costs of production to raise yields to 1,500 kg/ha.

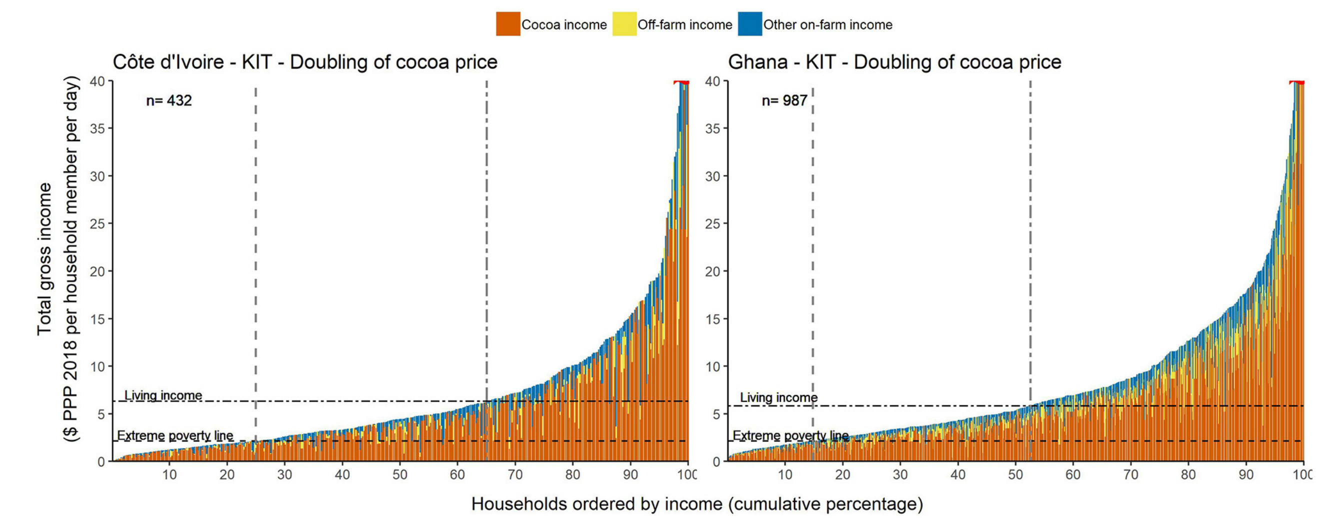

FIGURE 4 | Gross income per household member per day ($ PPP 2018) for each household of the KIT datasets when cocoa prices would double compared with the prices of 2015/2016, compared with the World Bank extreme poverty line and the Living Income benchmark based on Smith and Sarpong (2018) for Ghana and CIRES (2018) for Côte d'Ivoire.

extreme poverty line, with the highest percentages found in the WUR studies (58% in Ghana and 56% in Côte d'Ivoire). The vast majority of cocoa producing households fall below the Living Income benchmark: between 73% in Ghana (KIT) and 90% in Côte d'Ivoire (WUR). These outcomes reflect the findings of other studies, yet the exact figures are difficult to compare. For instance, the World Cocoa Foundation estimates that more than two-thirds of cocoa producers in some West African countries live below the poverty line (World Cocoa Foundation, 2020). This is higher than we find in any of the data sets studied, where we find percentages of household below the poverty line ranging from 30 to 58% (**Figure 2**; **Table 3**). However, we cannot be certain that the World Cocoa Foundation used the same poverty threshold. Peprah (2019) reports on a yearly gross cocoa income of 2,528 $ in Côte d'Ivoire, and 1,793 $ in Ghana (no year indicated), which is about 2–3 times less that estimated from the KIT study when assuming purchasing power parity has not been taken into account, and taking into account inflation. Other sources refer to total incomes of 0.78 $ pppd (Fountain and Hütz-Adams, 2018), 1.17 $ pppd (Balineau et al., 2016), or €0.46 pppd (Tony's Chocolonely, 2020), which again seem to be less than what we found. However, it is difficult to compare these income estimates as they are expressed in different (and often poorly-defined) units, it is not always clear whether they are based on gross or net income, how the number of household members has been defined, and whether all sources of income are

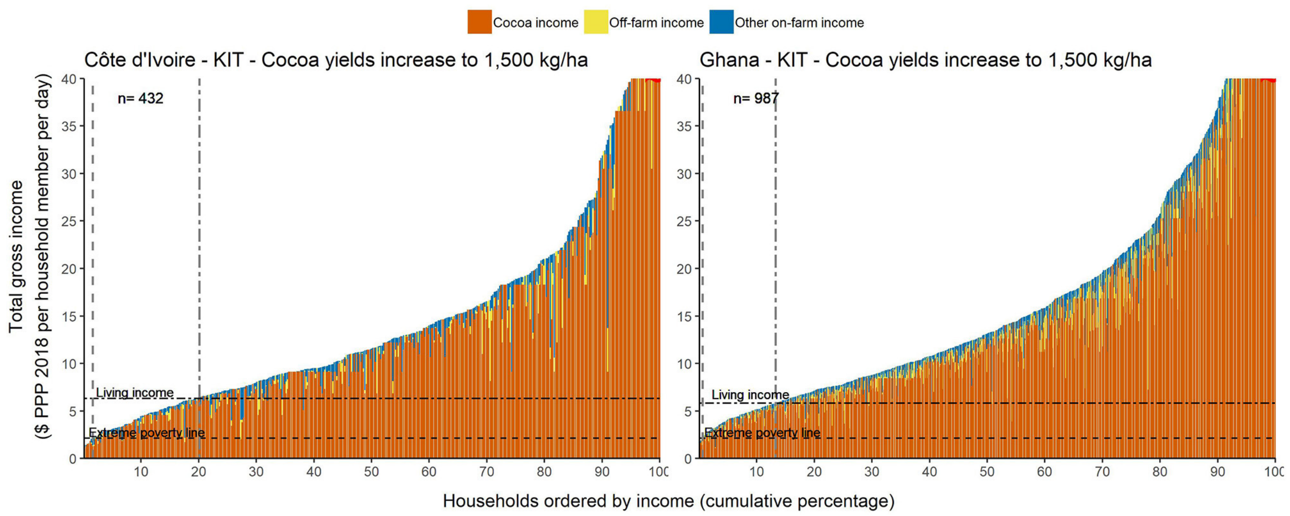

FIGURE 5 | Gross income per household member per day ($ PPP 2018) for each household of the KIT datasets when cocoa yields would increase to 1,500 kg/ha at the cocoa prices of 2015/2016, compared with the World Bank extreme poverty line and the Living Income benchmark based on Smith and Sarpong (2018) for Ghana and CIRES (2018) for Côte d'Ivoire.

accounted for. Further, differences among surveys and reports may be due to several factors, in particular the sampling frame which often includes only the farmers within a specific region or supply chain, and the topics and questions employed in the surveys. It would be very useful if a standard measure could be established for reporting of income, using the same assumptions and methodology across different studies.

Interestingly, Peprah (2019) refers to the World Bank (2017) for information on cocoa producer income, which in turn refers to the website of the Cocoa Barometer (https://www.voicenetwork.eu/cocoa-barometer/). They refer to the Cocoa Barometer of 2015, which states that their estimates are based on "extensive literature study" (Fountain and Hütz-Adams, 2015). The Cocoa Barometer of 2018 (Fountain and Hütz-Adams, 2018) is largely based on income data from the KIT study (Tyszler et al., 2018c) and a study commissioned by FairTrade (True Price, 2018). Cargill (2019) also refers to the KIT study for their estimate of the share of total income derived from cocoa. Overall, there seem to be few independent studies published regarding the income of cocoa producers, all of which conclude that most cocoa producers do not earn a Living Income and/or many earn below the poverty line.

Differences in Outcomes Among the Studies

There were large differences in the income distributions among the studies (**Figure 2**), although the overall patterns were similar. Mean and median income from cocoa pppd in the Cargill data was higher than in any of the other studies due to very high yields (**Table 3**). This is likely, at least in part, to be because all respondents were members of cooperatives in the "Cargill Cocoa Promise" program (**Table 1**). These farmers receive individual coaching and trainings. Nearly all of them are UTZ certified and receive a cash premium of 35 CFA/kg cocoa (**Table 1**). The good yields are likely the result from a combination of increased knowledge on good agricultural practices, and stronger motivation to invest labor and capital into cocoa production. To a lesser degree, this is also the case for the WUR data set of Côte d'Ivoire. Here, most respondents were members of producer groups who participated in the UTZ certification program, but did not receive individual coaching. The lowest mean and median yields in Côte d'Ivoire were found in the KIT data. Here, the cocoa producers are randomly selected and only 21% of the households in Côte d'Ivoire were members of a producer group (Bymolt et al., 2018). The variation in mean and median yields was much smaller among the data sets from Ghana, than those from Côte d'Ivoire. This may be caused by adverse weather conditions in Ghana for the 2015/2016 season, the data year for KIT (Reuters, 2015, 2016).

Another variable which differed widely among the data sets was the households' income from sources other than cocoa (**Table 3**; **Figure 2**), although not all surveys included this. The mean and median percentage of income from other sources was much smaller in the WUR data than in other data sets, contributing to the low total income. This could, again, be related to the group sampled or different ways in which the questions regarding income sources were framed. Total land availability, important for considering diversification options, was only available in the KIT data sets (**Table 3**). An overall conclusion however, is that greater availability of land, especially under cultivation, leads to a larger total income (**Figure 2**), both from cocoa and from other crops.

We conclude that the differences in variables underlying total gross income per person per day are for a large part caused by different target populations included in the surveys and framing of questions, as well as differences in cocoa prices and weather conditions between years. Unfortunately, not all variables were available for all data sets, prohibiting some comparisons.

Patterns in Farmer Incomes

Cocoa production is the largest source of income (about two-thirds or more in both countries, **Table 3**) for most households. Thus, as conceptualized in **Figure 1**, cocoa price, area and yield have a large effect on total income pppd (**Figures 3E,F**; **Supplementary Material 1**). In general the correlations among variables measured were fairly weak and should not be interpreted as indicative of causal relationships. The weak negative effect of cocoa area on cocoa yield (kg/ha) (in Ghana but not in Côte d'Ivoire, **Supplementary Material 1**) is probably related to a lack of capital and labor to invest in maintaining high yields on a larger area of land. In Ghana, where most of the available land is under cultivation and can therefore contribute to cocoa and other crop production, the effect of total available land on total household income is strong (**Figures 3C,D**). In Côte d'Ivoire, this relation is much weaker as much of the total available land is left fallow (median: 1.5 ha, mean: 2.6 ha against median: 0 ha, mean: 0.6 ha in Ghana). It seems that in Côte d'Ivoire, more households face constraints such as shortage of labor and capital which restrict the proportion of land that they cultivate. The higher labor shortage in Côte d'Ivoire compared to Ghana is confirmed by Odijie (2016) and attributed to higher labor needs in replanted cocoa than in first cycle cocoa on prior forest land.

Because large households generally have more productive household members, there is a positive correlation of number of household members with total household income. However, as they generally consist of relatively more dependents the relationship with income pppd is negative (**Figures 1**, **3A,B**). Household or family labor is the most prevalent source of labor for cocoa activities (Bymolt et al., 2018) as it is cheap and effective. Household labor can be supplemented or substituted when enough capital is available e.g., for hiring labor and/or applying herbicides (Van Vliet et al., 2015). In Ghana the relation between total household income and number of (productive) household members is much weaker than in Côte d'Ivoire. In Ghana, more use is made of hired labor and herbicides (Bymolt et al., 2018). As a result, household labor is less of a constraint to increasing household income than in Côte d'Ivoire.

Overall, the results of these analyses are consistent with the conceptual scheme presented in **Figure 1**, suggesting the importance of self-amplifying mechanisms. Households with a higher income are more likely to be able to afford to invest in production through accessing inputs and hiring labor, giving them access to a larger total labor force and therefore gain a higher income (**Figure 1**). By contrast, the low cocoa price, low cocoa yields, lack of income from other sources, low availability of land, and large households with relatively many dependents result in poverty traps for the poorer households (**Figure 1**).

Options to Increase Income of Cocoa Producers

Here, we focus on three determinants of household income which are prominent in the causal diagram (**Figure 1**): the cocoa producer price, cocoa yields, and other sources of income (diversification on or off the farm).

Scenario 1: Increasing Cocoa Prices

The Living Income Differential recently imposed by the governments of Côte d'Ivoire and Ghana leads to a producer price of 1,820 USD per ton. This is virtually the same as the producer prices in 2015/2016 when expressed in $ PPP 2018, so when changing the prices of 2015/2016 to those resulting from the Living Income Differential for 2020/2021 there is little to no effect on farmer incomes (**Table 4**). We went on to explore the relative impact on different households of a more drastic scenario of doubling cocoa prices. Although this clearly represents a substantial increase, for comparison it is only 14% more than the minimum cocoa producer price of 3,000 US $ per ton which the Voice Network deems necessary for cocoa producers to earn a Living Income (Fountain and Hütz-Adams, 2019). Such a price increase significantly improves the incomes of the already better-off producers. They generally produce large volumes of cocoa due to large cocoa land area and/or good yields, and therefore a price increase would have a large impact on their income. For the poorest whose total cocoa production is limited due to small land areas and/or low yields the impact is much less visible. Of course, even a small increase in income would be of great value to the poorer households, but insufficient to provide a Living Income or raise them above the poverty line.

Scenario 2: Increasing Cocoa Yields

We explored a scenario in which all cocoa yields increase to 1,500 kg/ha, using the KIT survey data (Scenario 2). Although few producers currently achieve such yields, it is a fairly modest target compared with the crop's technical potential (Zuidema et al., 2005; Van Vliet and Giller, 2017). As explained in the introduction there are several examples where smallholders have achieved cocoa yields well above 1,500 kg/ha, although in the Cargill surveys, only 1.4% of 86,380 producers achieved yields of 1,500 kg/ha or more. Yields generally achieved by farmers are around 300–400 kg/ha, except in the Cargill sample where mean yields are close to 600 kg/ha (**Table 3**). It would be worthwhile to further investigate the factors underlying these relatively high yields.

Increasing cocoa yields to 1,500 kg/ha leads to a large increase in gross income across households. Only 1–2% of households fall below the poverty line in this scenario, and only 14–20% remain below the Living Income benchmark (**Table 4**). The income benefits are largest for the poorer producers because they often have the lowest starting yields (**Figures 2E,F**); about 70% of those living below the poverty line have yields below 250 kg/ha. Therefore, for them the increase in income resulting from the yield increase is largest. We also calculated the effects of more modest yield increases to 600, 800, or 1000 kg/ha (**Table 4**). Even an increase to only 600 kg/ha has a stronger effect than doubling cocoa price on the proportion of households above the poverty line or those earning a Living Income. This further suggests that increasing income through yield intensification has larger benefits for the poorest farmers than increasing prices.

However, the poorest producers also face the greatest challenges to increase their cocoa yields. Investment is needed to intensify production through increased management (e.g., pruning, weeding, frequent harvesting) and inputs (e.g., fertilizers, pesticides) and, in the longer term, perhaps even replanting (Aneani and Ofori-Frimpong, 2013; Kongor et al., 2018; Abdulai et al., 2020). All of these require resources such as capital and labor to which these producers often lack access (**Figure 5**, Fountain and Hütz-Adams, 2018, 2019). Although there is a positive correlation between expenditure on inputs and yields (**Supplementary section S3**), it is difficult to estimate the increase in expenditure required to increase yields to 1,500 kg/ha. Clearly, required investments per ha will be greatest for farmers with the lowest current yields, who are often the poorest (**Figures 2E,F**). Moreover, return on investments is unpredictable and producers may not be able to bridge the time between investments and benefits (Assiri et al., 2012; Ruf and Bini, 2012). We explored the effects of an extra scenario in which 30% of the income generated by increasing yields to 1,500 kg/ha was absorbed by the increased costs of production. This results in 12% more farmers earning less than the Living Income threshold (32% of the farmers) compared with a yield increase without the additional investment of 30% (20% of the farmers; **Table 4**).

Broader Impacts of Increasing Cocoa Prices and Yields

If the cocoa price or cocoa yields are increased as explored in the scenarios presented above this will undoubtedly have wider short and long term implications for the cocoa production sector as a whole. An increase in the cocoa price will both stimulate and enable producers to increase their yields, potentially resulting in larger income increases than those suggested here (**Figures 4**, **5**). Both strategies may also provide an incentive for farmers to expand their cocoa area within their farms, replacing other crops or fallow land and reducing non-cocoa income. In the absence of strong governance, the economic incentives could also encourage expansion of cocoa production into forests (Wessel and Quist-Wessel, 2015; Fountain and Hütz-Adams, 2018). Increases in the overall amounts of cocoa produced lead to a surplus of supply and decreases in the world market price if demand does not increase at the same time, as has happened in the 2016/2017 cropping season (Fountain and Hütz-Adams, 2018). Both price and yield increases, therefore, may backfire unless policies are in place to manage international supply (Koning and Jongeneel, 2006; Fountain and Hütz-Adams, 2018). Such policies are only effective when producing countries join forces and set the necessary conditions. Options to do this include setting export quota and tariffs, liaising with producer organizations, assisting some producers to move out of cocoa to other sources of income (Odijie, 2018), paying producers a premium independent of their production, preventing countries from free riding, and perhaps even destruction of surpluses (Koning and Jongeneel, 2006). When such policies are in place, it may be safe to slowly allow production to increase, as global demand for cocoa continues to rise (ICCO, 2012, 2020).

Income Diversification

Another option which is frequently proposed is for cocoa producers to diversify their income, both on-farm and off-farm (Barry Callebaut, 2018; Cargill, 2019). On-farm income diversification implies including more (tree) crops or livestock on the farm, or adding value to farm products before they are sold. This leads to less reliance on a single (cash) crop and therefore reduces risks, which is especially important given the price volatility of cocoa and other commodities (Schroth and Ruf, 2014; Bymolt et al., 2018; Fountain and Hütz-Adams, 2018). Shifting to other (tree) crops and agroforestry are also potential adaptation strategies in the face of climate change, which already appears to reduce the area suitable for cocoa production in West Africa (Läderach et al., 2013; Fountain and Hütz-Adams, 2018; Abdulai et al., 2020). Furthermore, on-farm diversification can increase household food security due to improved seasonal and long-term stability of on-farm production, and improved dietary diversity either directly through consumption of farm produce or indirectly through increasing the income available to purchase food (Fountain and Hütz-Adams, 2018; Feliciano, 2019).

Cocoa-producing households in Ghana and Côte d'Ivoire already grow five (Ghana) or six (Côte d'Ivoire) different crops on average (Bymolt et al., 2018). In the KIT data, on average 67% (Côte d'Ivoire) or 62% (Ghana) of income is derived from cocoa, indicating they are not as dependent on cocoa as suggested by other studies (**Table 3**, True Price, 2018). Dependency on cocoa appears to be only weakly linked to poverty, so diversification does not necessarily lead to a higher income (**Figures 2G,H**). Moreover, the initial investment required might limit diversification to better-off households (Feliciano, 2019). Lack of additional land and labor may also prohibit on-farm diversification (**Figure 1**). Tree crops such as cocoa are fixed assets which take time and capital to be replaced (Aneani et al., 2011; Schroth and Ruf, 2014). Cocoa producers cannot respond quickly to market or climatic signals and are only likely to move away from cocoa when benefits from other (tree) crops are higher for a prolonged period of time (Aneani et al., 2011; Schroth and Ruf, 2014; Abdulai et al., 2020). Cocoa is perceived by cocoa producers to be their most profitable crop in Ghana and Côte d'Ivoire, and if anything, the importance of cocoa has increased in recent years (Bymolt et al., 2018). Households have a variety of economic and non-economic reasons to diversify and choose different crops, such as distribution of income and labor requirements over the year, suitability for household consumption, reliability of the market and other infrastructure, public policy, land availability, and tradition (Schroth and Ruf, 2014; Bymolt et al., 2018; Feliciano, 2019). Whether further diversification is profitable and desirable depends on the household's resources (e.g., land, capital, and labor) and on the enabling environment (e.g., infrastructure and marketability) (**Figure 1**, Bymolt et al., 2018).

Off-farm income may help to spread risk, and can complement farm income in the low season (Alobo Loison, 2015). Furthermore, off-farm income may provide potential for on-farm investments (leading to increased yields) and *vice versa* (Alobo Loison, 2015). Especially for those households with little land, off-farm diversification may be required to increase income (Feliciano, 2019). Unfortunately, poorer households are often less able to engage in high-return off-farm activities, e.g., salaried jobs, as they lack the starting capital and/or education required (Alobo Loison, 2015). Thus poorer households are often forced to engage in seasonal casual labor jobs, which are less beneficial to household welfare (Dzanku, 2015). Off-farm diversification requires an enabling environment including improved infrastructure, proximity to urban areas, access to education, and increased demand for non-food goods and services driven by higher per capita incomes (Alobo Loison, 2015). We found that the proportion of off-farm income is generally low, though it is higher in Ghana (mean = 17%, median = 10% in the KIT data set) than in Côte d'Ivoire (mean = 10%, median = 0% in the KIT data set) (**Figure 2**).

Overall, the scope for cocoa producers to increase their income through diversification seems limited. Cocoa is perceived as one of the most profitable crops, and especially for the poorest households, a lack of opportunities and resources prevents them from engaging in more attractive income-generating activities.

When devising strategies to help cocoa producers to increase their income, knowledge on the availability of land (family), labor, and capital, and any constraints faced regarding these resources is crucial as the suitability of options depend on availability of these resources. More in-depth research regarding the possibility and willingness to invest these resources is required to understand which options are most suitable for which households.

Suggestions for Future Surveys

Household survey data is pivotal to underpin our understanding of the income of cocoa producing households and the opportunities and constraints they face. Currently, different companies and organizations make huge investments in household monitoring, surveying thousands of households each year. The surveys of KIT and Ghent University aimed to gain insights into the overall population of cocoa-producing households in each country. By contrast the surveys conducted by WUR and Cargill were focused on cocoa producing households working within specific companies, certification schemes, or cooperatives, with the aim of providing baseline information against which changes could be monitored over time. The more general utility of such surveys would be enhanced if questionnaires are standardized and attention is paid to variables that are often overlooked, or for which only superficial information is collected.

Increasing cocoa yield is a key leverage point to increase household income (**Figures 1**, **5**). In general, input costs per hectare (excluding labor costs) rise with increasing yields (see **Supplementary Material 1**), but the relationship is weak. In particular, more robust quantitative and qualitative information on the intensity and cost of input use and management practices is needed.

We were not able to include the contribution of food crops grown for household consumption or other sources of in-kind income to meet household needs in our analysis of household income. This is a shortcoming, given that food cost may comprise about half of household expenditure in less-developed countries when assuming all food is purchased (Donkoh et al., 2014; CIRES, 2018; Smith and Sarpong, 2018; Van De Ven et al., 2020). Such information is difficult to collect given the detail required, but excluding it may lead to a substantial underestimation of income for some households. More data could be collected to understand the dynamics of sharecropping, such as the division of costs, decision making, rights, and income from the sharecropped land between the sharecropper and the owner of the land. Especially in Ghana, many households are sharecroppers: 32–49% of the respondents were sharecroppers on at least part of their cocoa land, leading to an overestimation of household income (based on the data from KIT, WUR, and Ghent University). By contrast sharecropping was rare in Côte d'Ivoire, reported by only 1–5% of the respondents (based on the data from KIT and WUR). Besides data related to cocoa production, data on other sources of on-farm and off-farm income is required. This includes information on the cultivation and marketing of other crops and land availability. Other variables of importance are availability and (opportunity) costs of household and hired labor.

To allow a more accurate comparison of households of different compositions to the Living Income benchmark, Van De Ven et al. (2020) suggest that the Living Income benchmark should be expressed on an AE basis. We found little difference in the number of households obtaining a Living Income when we recalculate the income data and the Living Income benchmark to income per AE rather than per person (**Supplementary Material 2**). Standardization of household surveys, using a common ontology of definitions, units, and variables included, and sharing data would enhance the utility and interpretability of the data collected, and reduce the effort and costs of all parties. Ultimately, this would lead to a better understanding of the households producing cocoa which will support the development of strategies to increase their income. The Rural Household Multi-Indicator Survey (RHoMIS; Hammond et al., 2017) provides an excellent basis for such a standardized survey questionnaire.

CONCLUSIONS

Our analysis shows that most cocoa producing households in Côte d'Ivoire and Ghana have difficulties to achieve a Living Income, and many fall below the poverty line. To allow comparisons among households, we expressed income on a per person basis. The key factors that determine income include the cocoa price, cocoa yields, number of household members, the land area on which cocoa is cultivated, and the contribution of non-cocoa income streams. To address poverty among cocoa producing households, the need to increase the price paid for cocoa to the producers is often emphasized. Our scenario analysis suggests that price increases will have limited effects on the income of households who now struggle the most, while benefits will mainly accrue to those who already earn more from cocoa. Of course this does not diminish the need to increase prices paid to farmers: currently, only 7% of the price consumers pay for chocolate reaches the cocoa producer (Solidaridad, 2020b).

Cocoa remains an important income stream even of the poorest producers. Yet, it is important to realize that even drastic increases in the price of cocoa will not lead to an end of poverty for all cocoa producers.

Currently many research and development programmes focus on the sustainable intensification of cocoa production. By contrast with increases in price, poorer households stand to benefit the most from increases in productivity, as they often have the smallest current yields. However, especially poorer producers often lack the capital and labor required to achieve substantial increases in yield, and such investments pose a large risk.

Even when all possible strategies are considered, structural changes will be required in the long term to lift all producers out of poverty. Moreover, both income and yield increasing strategies would lead to increases in cocoa production which will lead to price drops when no international supply management policies are implemented. Besides conditions such as setting international export quota and tariffs, structural changes could include land reform (to increase farm sizes) in combination with adequate opportunities for off-farm income generation. These structural changes are not the sole responsibility of the companies involved in cocoa procurement. Concerted action is needed from the sector together with local and national governments to sustainably increase the income situation of cocoa producers in West Africa. Such action will need to be based on a shared assessment and understanding of the current income situation and resource availability of cocoa producers, underpinned by relevant and reliable data. To enhance utility and interpretability of household surveys and other data collection tools, we recommend that companies and organizations collecting farmer data develop a standardized set of (survey) data to be collected using a common ontology of definitions, units, and variables. Such advancements in the depth and standardization of data collection can then support the development of strategies to improve the incomes of cocoa producers and the sustainability of the cocoa sector as a whole.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi10.7910/DVN/82TWZJ.

AUTHOR CONTRIBUTIONS

JvV and KG conceived the study. JvV conducted the analysis with guidance from KG and MS. JvV, KG, MS, and YW wrote the paper. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2021.732831/full#supplementary-material

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AgroFIMS: A Tool to Enable Digital Collection of Standards-Compliant FAIR Data

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Agricultural research has been traditionally driven by linear approaches dictated by hypothesis-testing. With the advent of powerful data science capabilities, predictive, empirical approaches are possible that operate over large data pools to discern patterns. Such data pools need to contain well-described, machine-interpretable, and openly available data (represented by high-scoring Findable, Accessible, Interoperable, and Reusable—or FAIR—resources). CGIAR's Platform for Big Data in Agriculture has developed several solutions to help researchers generate open and FAIR outputs, determine their FAIRness in quantitative terms[1], and to create high-value data products drawing on these outputs. By accelerating the speed and efficiency of research, these approaches facilitate innovation, allowing the agricultural sector to respond agilely to farmer challenges. In this paper, we describe the Agronomy Field Information Management System or AgroFIMS, a web-based, open-source tool that helps generate data that is "born FAIRer" by addressing data interoperability to enable aggregation and easier value derivation from data. Although license choice to determine accessibility is at the discretion of the user, AgroFIMS provides consistent and rich metadata helping users more easily comply with institutional, founder and publisher FAIR mandates. The tool enables the creation of fieldbooks through a user-friendly interface that allows the entry of metadata tied to the Dublin Core standard schema, and trial details *via* picklists or autocomplete that are based on semantic standards like the Agronomy Ontology (AgrO). Choices are organized by field operations or measurements of relevance to an agronomist, with specific terms drawn from ontologies. Once the user has stepped through required fields and desired modules to describe their trial management practices and measurement parameters, they can download the fieldbook to use as a standalone Excel-driven file, or employ *via* free Android-based KDSmart, Fieldbook, or ODK applications for digital data collection. Collected data can be imported back to AgroFIMS for statistical analysis and reports. Development plans for 2021 include new features such ability to clone fieldbooks and the creation of agronomic questionnaires. AgroFIMS will also allow archiving of FAIR data after collection and analysis from a database and to repository platforms for wider sharing.

Keywords: agriculture, fieldbook, standardization, digital, FAIR

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[1] https://gardian.bigdata.cgiar.org/metrics.php#!/

INTRODUCTION

Agricultural researchers are increasingly exploring machine learning and other predictive approaches to formulate appropriate interventions. Technology developments such as Internet of Things and Cloud Computing together with Big Data capabilities are driving "Smart Farming" (Sundmaeker et al., 2016; Nidhi, 2020), enabling decision-making based on location and other contextual and situational data in real-time (Wolfert et al., 2017). These capabilities and aspirations require that complex and often inter-disciplinary datasets—small and "big"—be easily queried, mined, aggregated and analyzed to derive insights and actionable options (Hashem et al., 2015). By accelerating the speed and efficiency of research, these approaches can facilitate innovation, allowing agile responses to challenges in the agricultural sector.

Farmer access to timely, accurate, hyperlocal recommendations is one such challenge; in response, agriculture is becoming increasingly digitized, and digital advisories are blossoming, particularly in low- and middle-income countries (Tsan et al., 2021). In 2020 the GSMA AgriTech program was tracking over 700 active digital agriculture services that supported and provided services to smallholder farmers, up from just 53 in 2009. These included digital advisories focused on best management practices, as well as financial, procurement, e-commerce, and other options either as individual or bundled services (Phatty-Jobe, 2020). Digital advisory services depend on reliable, location-specific data to offer management options that can improve crop yields and profitability, taking into account local biophysical conditions. While big data capabilities can offer analytics to power digital advisories and facilitate innovation in agricultural research, and agility and impact in the solutions space for farmers and other stakeholders, they rely on standardized, machine-interpretable agronomic data.

An exemplar of the power of open, interoperable data is the COVID-19 Open Research Dataset (Semantic Scholar, 2021) with the use of widely accepted standards such as mature biomedical ontologies (Bodenreider et al., 2005) enabling such advances. The collaborative application of massive computing power to this shared data and standards enabled researchers to model and identify promising compounds for treatment in just under two days—a result that would otherwise have taken years (Quitzau, 2021). This is a powerful demonstration of *in silico* analysis over vast data pools enhancing the speed and scale of scientific innovation, and a similar model could be just as ground-breaking for millions of agricultural practitioners. This necessitates mining pools of agriculture-related publications, data, and data products that are fully open, interoperable and reusable, adhering to the FAIR Data Principles (Wilkinson et al., 2016). With the exception of the genomic/genetic disciplines, the agricultural domain in general has lagged in this regard. Most agronomic datasets are collected as activities under individual projects, following project recommendations at best, resulting in bespoke data terminologies and annotations, uneven or non-existent metadata, and other issues that make it difficult to share, reuse, or aggregate such data.

CGIAR[2] is a large network of global agricultural research for development centers working globally with partners and farmers in several of the poorest nations. CGIAR's Platform for Big Data in Agriculture[3] has developed many open-source tools and solutions to help agricultural researchers anywhere generate open and FAIR outputs easily and quickly, and to create high-value data products drawing on these outputs. Its GARDIAN data ecosystem[4] includes a toolkit with a FAIR data workflow, for instance, that helps make legacy data assets FAIR. In these endeavors data interoperability tends to be the more difficult aspect to address, and it has become clear that it is most efficient to generate data that is interoperable "at birth" and also as findable as possible. The CGIAR Platform for Big Data in Agriculture developed the Agronomy Field Information Management System or AgroFIMS[5] in response, to enable the collection of agronomic data that is highly interoperable and findable, helping users with some of the more challenging aspects of FAIR data.

AgroFIMS is a web-based, open-source tool that allows users to create fieldbooks which can be exported to several free digital collection Android apps, including KDSmart[6], Open Data Kit[7] (Hartung et al., 2010), and Fieldbook[8] (Rife and Poland, 2014). The fieldbooks include metadata already tied to a standard [the CG Core Metadata Schema,[9] aligned with the industry standard Dublin Core (Apps, 2005)], and data variables that are linked to concepts in semantic standards like the Agronomy Ontology [10] (AgrO). Users do not need to know details about standards such as ontologies, as the terms they choose are part of their normal scientific and agronomic domain vocabulary. By employing these data standards toward annotation *a priori*, AgroFIMS helps to create a semantic pool of data for easy aggregation and leveraging by machine learning and other technologies. AgroFIMS also generates rich metadata that largely adheres to semantic standards and controlled vocabularies, facilitating compliance with growing institutional, founder and publisher mandates for FAIR data through this focus on interoperability and findability. Although users are encouraged to use the least restrictive licensing possible, the tool itself does not force licensing choices on users. In-development efforts will make it easier for users to choose appropriate standard licenses for access and data reuse. To further encourage more accessible and reusable data, by the end of 2021 AgroFIMS will call on aspects of the GARDIAN FAIRscribe to provide a score indicating how FAIR data is, allowing the user to address low-scoring dimensions.

[2]https://www.cgiar.org/
[3]https://bigdata.cgiar.org/
[4]https://gardian.bigdata.cgiar.org/
[5]https://agrofims.org/
[6]http://www.kddart.org/kdsmart.html
[7]https://getodk.org/
[8]https://play.google.com/store/apps/details?id=com.fieldbook.tracker&hl=en&gl=US
[9]https://github.com/AgriculturalSemantics/cg-core
[10]https://bigdata.cgiar.org/resources/agronomy-ontology/

METHOD

AgroFIMS Framework

AgroFIMS allows users to easily design and create fieldbooks to collect agronomic data already tied to a metadata standard, the CG Core Metadata Schema, and calling on ontologies to populate metadata fields. The tool was first developed in 2018, but its features and user interface have undergone iterative improvements based on testing and feedback by agronomists, crop modelers and developers. It now offers an intuitive platform to guide users through different screens following the schema of a typical agronomic experiment. AgroFIMS then aggregates this information in an easily usable data collection form or *fieldbook*.

The general workflow for an AgroFIMS user starts with fieldbook creation and ends with data publication in one of many repository platforms (**Figure 1**). The first step of this workflow, the design of a fieldbook, is done online on the AgroFIMS website (**Figure 2**), and involves filling the *Metadata module* that allows users to specify where the agronomic trial will be conducted by defining one or more sites *via* the *Site*s tab. The tab allows users to specify and manage trial locations, with site metadata (including latitude, longitude, elevation, administration level names etc.) introduced in a web form that displays and zooms a map. To add a new site, users enter administrative division names, the GPS coordinates or pinpoint the site on this map (**Figure 3**). GADM Maps and Data[11] is used to define administrative levels (countries and their sub-divisions). The newly created site is then saved in AgroFIMS and can be connected to experiments. A site is the entry point for any fieldbook in AgroFIMS.

The next step of the Metadata module involves defining an agronomic experiment or trial with experiment details, representing trial metadata (**Figure 4**). The experiments are assigned unique identifiers by the system and are accessible only to the person who designed them, they are not shared across AgroFIMS users. To create an experiment, users give it a name and add details about the project and its objectives, grant information, funding agency, management entity and/or lead. A tab dedicated to personnel working on the experiment auto-loads the user's information and allows registration of different team members and their roles in the trial.

A new fieldbook can now be added to the experiment. One or more fieldbooks may be included in the same experiment as part of a project, allowing multisite and multiyear experiments. For each new fieldbook, a suite of tabs allows the user to describe the experiment in standardized terms. For instance, a *Crops* tab lists 21 possibilities (cereal crops, root and tuber crops, and more), allowing users to choose one or more crops from existing ontologies that will be part of the experiment—or to specify a crop not in the list. Users can also indicate varieties of the crop/s chosen and whether the trial will involve a monocrop, intercrop or relay crop.

Subsequently, in the *Design and protoocl module* (**Figure 2**) the user can define a statistical design from a list of 7 common agronomy-relevant designs (**Figure 5**), and specify experimental unit (plot, field, pot), treatment description and factors.

The *Variables module* of AgroFIMS (**Figure 2**) is the foundation for tabs allowing the user to define the data they want to collect in the field, and how these data should be collected: sampling points/applications per season and/or plot (e.g., for irrigation), unit of measurement, plant part to be sampled, sampling time interval (e.g., plant growth stage, days after planting, frequency, or other). Measurements to be made in the field or in the lab are specified, organized by crop, phenology, weather and soil. Where relevant, the number of measurements to be made per plot and/or per season can be indicated, with sampling timing as described earlier. Protocol details can be indicated *via* auto-complete functionality from picklists organized by operation type, and including information like the number of tillage passes, type of implement, depth and timing of tillage, and more. The user can also toggle an "actual" vs. "planned" protocol button to indicate how certain operations are to be done. A separate Fertilizer tab is defined to specify product or nutrient types, formulations, and amounts to be applied from a list of 130 possible fertilizer products. A special pop-up module facilitates the calculation of fertilizer quantity to apply, along with implements to be used, timing of application/s and more. This feature is described in the Results section (**Figure 7**).

AgroFIMS supports either spreadsheet or mobile-based data collection, and once a fieldbook is completed it can be downloaded in different formats: .xlsx, .kdx, .csv, .trt and .xml. The mobile format is tailored for three freely available Android applications: KDSmart,[12] Fieldbook[13] (Rife and Poland, 2014), and ODK Collect[14] (Hartung et al., 2010). Excel displays the metadata added in the AgroFIMS website as the first tab, with other tabs based on field protocols, crop, soil, and weather measurements, and traits specified. Digital data collection eliminates the need to transcribe from paper to digital format and reduces errors thanks to the validity range applied to each measurement. Collected data can be uploaded every day making it possible to assure and course-correct to ensure that an experiment follows the planned trajectory.

Once data is collected, files can be exported in a Google spreadsheet from ODK, and as a zip file from Fieldbook. Users of KDSmart can export collected data back to AgroFIMS for analysis using a statistical analysis module compatible with the application (**Figure 1**). File outputs from KDSmart are uploaded to AgroFIMS to generate a statistical report in a Word format and based on R scripts. Datasets can then be saved in institutional repositories (**Figure 1**). This step is currently done manually, but direct upload from AgroFIMS to repositories through an Application Program Interface (API) will soon be available. A help

[11] https://gadm.org/

[12] http://www.kddart.org/kdsmart.html

[13] https://play.google.com/store/apps/details?id=com.fieldbook.tracker&hl=en&gl=US

[14] https://getodk.org/

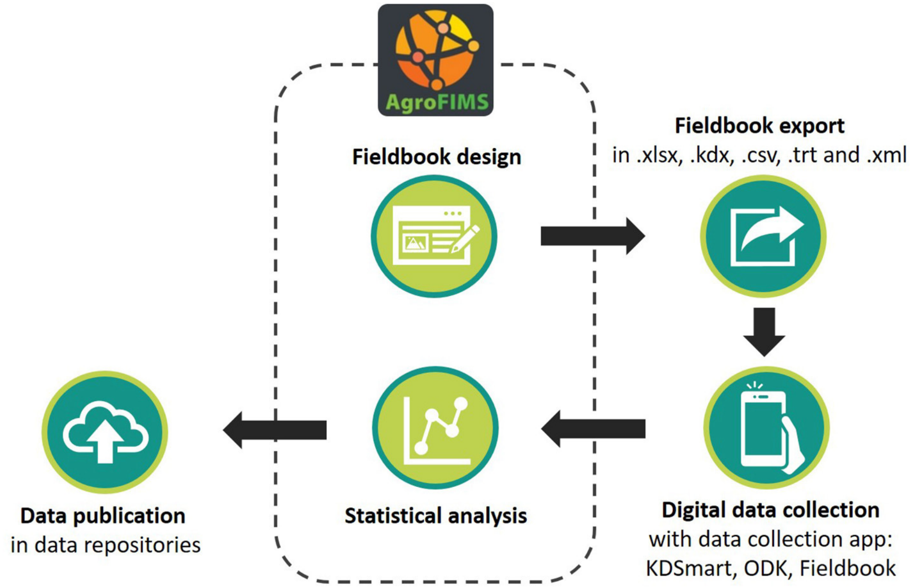

FIGURE 1 | Steps to design a fieldbook and manage agronomic dataset using AgroFIMS.

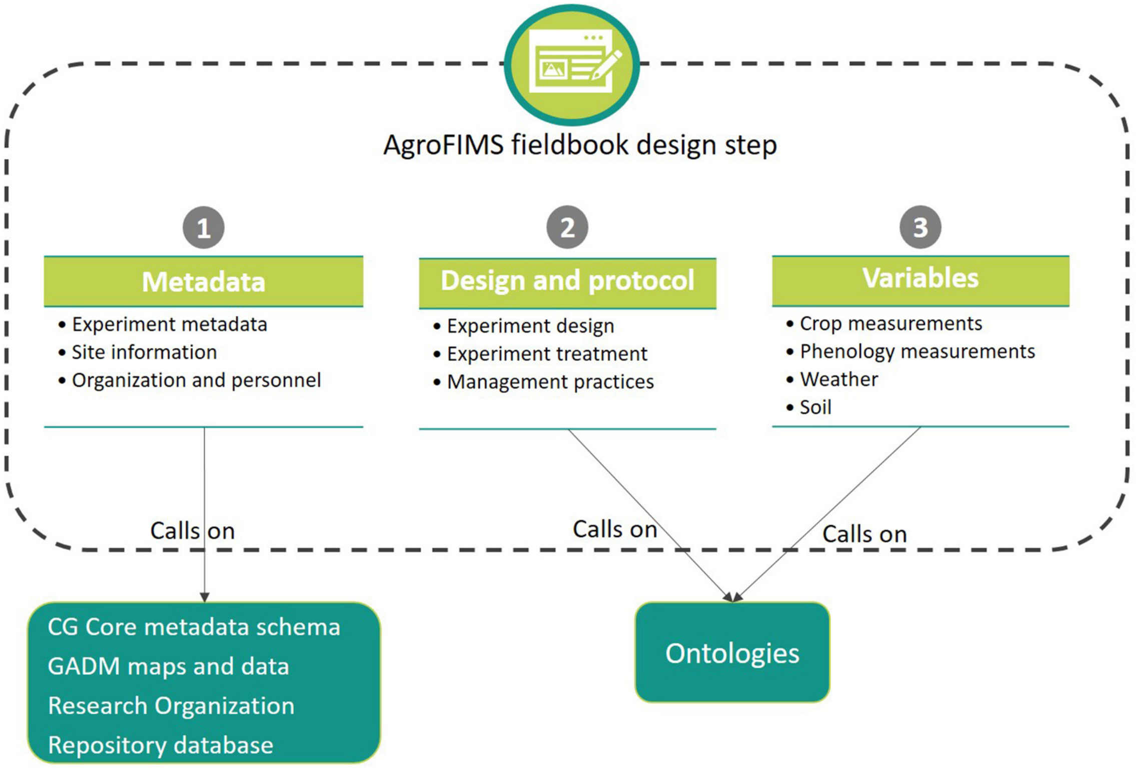

FIGURE 2 | Main modules and their subcomponents of AgroFIMS ''fieldbook design" step.

page[15] has been designed to support the use of AgroFIMS (Aubert et al., 2020).

[15]https://agrofims.github.io/helpdocs/

Technical Specifications

The AgroFIMS platform initially began as an interactive analytics platform for breeding trials, developed in the R statistical language. It was expanded to be a more complex data collection

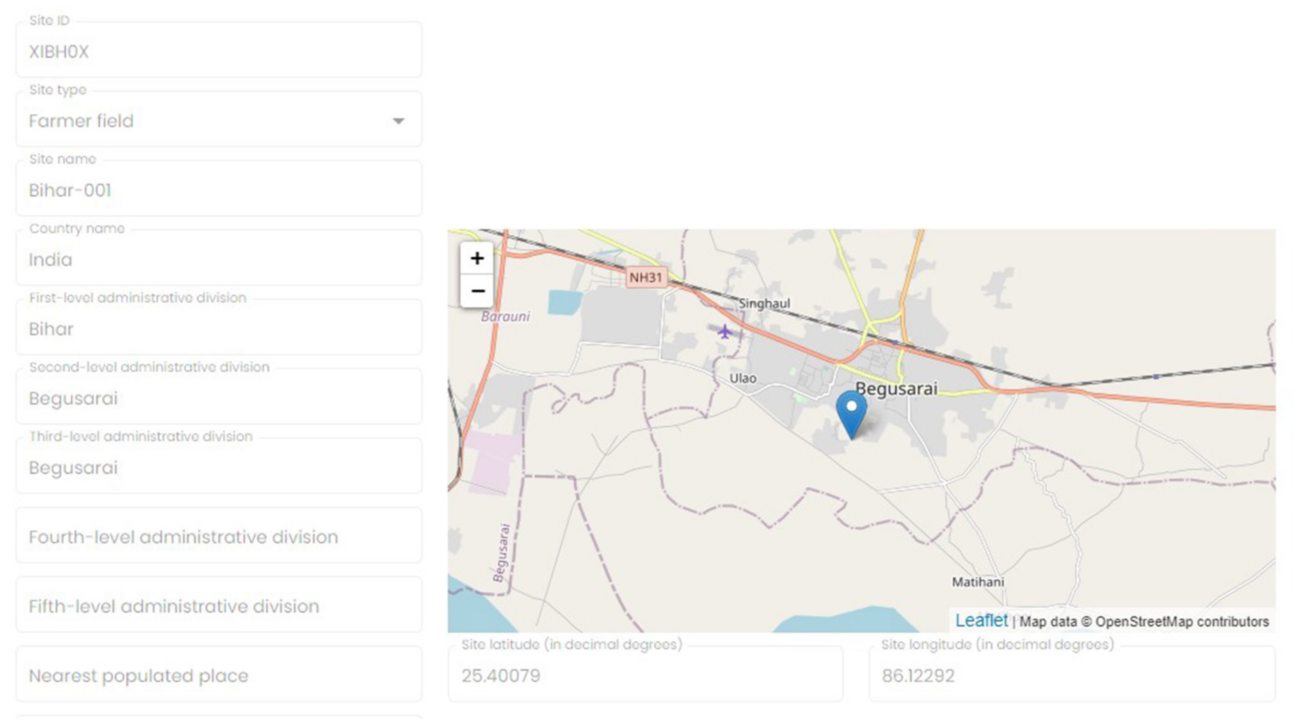

FIGURE 3 | Sites can be specified by choosing country and administrative divisions from an authoritative database connected into AgroFIMS, or by dropping a pin on a map.

tool that is developed on top of Angular 11.0, a single web-based page application framework maintained by Google and compatible with multiple browsers (Google, 2020). The application source code is maintained on GitHub,[16] where all commits, changes, and enhancements in the source code are tracked.

The single web-based page application permits building data-driven and form-intensive applications such as AgroFIMS. The AgroFIMS frontend comprises one to multiple complex forms and auto-save forms functionality, everything based on Angular. The frontend communicates with the backend, which is developed in PHP and TypeScript (NodeJS), *via* web services establishing a connection to the database. The backend contains the queries that bring the required data from the database. This data is presented in the user interface through AgrAPI. APIs are configured to carry the information through URLs in JSON. The database uses MySQL as the database engine to manage data through tables, using a relational model. The database stores information from the auto-save functionality to restore sessions, and agronomic data dictionaries.

The web architecture of AgroFIMS follows REST (REpresentational State Transfer) specifications, widely supported by modern web services (Fielding and Taylor, 2002). An API is defined over this for data exchange between users and services to handle agronomic data in the platform. This REST API called AgrAPI addresses the problem of accessing large and complex datasets, enabling access, integration and exchange of FAIR agronomic data across systems and applications (Leonelli et al., 2013). AgrAPI calls have been organized to mirror the operational structure of AgroFIMS *via* categories

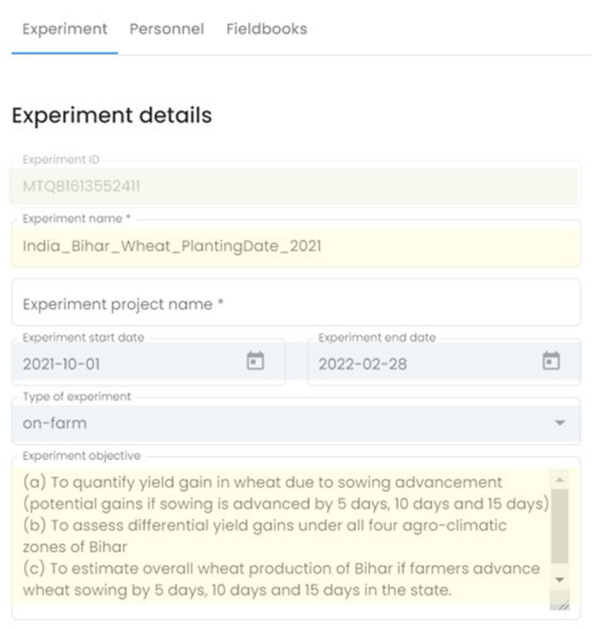

FIGURE 4 | Example of experimental details form in AgroFIMS, showing a mix of system-generated information (light green); standardized choices (light blue); and user-entered text (pale yellow).

[16] https://github.com/AGROFIMS/agrofims-angular-code

such as experiment details, site details, crop, design, fertilizer, management practices, field measurements and environmental variables (**Table 1**).

AgrAPI calls are implemented through an R-package called ragrapi[17] This package is aimed at accessing all the relevant data defined in AgrAPI, retrieving information about an experiment, getting field layouts, searching for fertilizer data, and accessing the different variables of the agronomic experiment.

Ontology Underpinnings

Data interoperability between fieldbooks from the same experiment and across experiments is a critical need to enable the creation of data pools that can be easily mined and harnessed to analytics. Interoperability tends to be the biggest challenge in data FAIRification, requiring standardization that can be achieved with semantic technologies, including ontologies. An ontology is a formalized organization schema that allows classification and organization of concepts in a knowledge domain, and that makes explicit the relationships and hierarchies amongst these concepts to provide semantic context. Every term is associated with a Uniform Resource Identifier or URI, a short string of characters that identify resources in the web, making it clear to machines what the term means, and the broader context in which it resides based on the hierarchy it is part of. While ontologies offer powerful capabilities, they are not easy to leverage. AgroFIMS makes it easy for agronomists to use these and metadata standards without necessarily knowing the particulars of the standards themselves, as described below.

AgroFIMS relies on the Agronomy Ontology[18] (AgrO) to enable standardization of data variables and parameters, and thus, interoperability across multiple datasets. AgrO includes approximately 2270 terms depicting the agronomy domain (as of June 2021). These are semantically organized and can facilitate the collection, management, understanding, sharing and use of agronomic data, enabling easy interpretation and reuse of the data by humans and machines alike. AgrO follows OBO Foundry principles,[19] and therefore builds on existing standards. It relies on traits and parameters identified by agronomists and avoids replication of concepts already in other ontologies and vocabularies by including them with their native URIs. Some indicative standards that AgrO draws from include the ICASA Data Dictionary (White et al., 2013), and other existing ontologies such as the Environment Ontology (Buttigieg et al., 2016), the Unit Ontology,[20] the Trait Ontology (Cooper et al., 2020) and the Crop Ontologies (Shrestha et al., 2012), as illustrated in **Figure 6**, which shows a small part of AgrO. Like many other ontologies, AgrO is enriched through knowledge provided by scientists working in the agronomy domain, allowing it to realistically describe and model agronomic experiments including agricultural practices and implements, and variables that are typically measured during the experiment, from soil and weather to crop and fertilizer.

All terms that a user selects in AgroFIMS are linked to AgrO classes. For instance, when the plot length is given in meters on the web interface, the value is automatically annotated to both the AgrO class AGRO:00000337 ("plot length") and the Unit Ontology UO:0000008 (meter). The user does not have to know anything about ontologies to end up getting annotated data. In the near term, when a user downloads an Excel fieldbook, the annotations would be available in the column header, in addition to the variable name. To flag a parameter that is not in AgroFIMS or AgrO, a request would be sent from AgroFIMS to an issue tracker being built to link with AgrO. The data will not be annotated immediately as the request would need to be processed by ontology curators, but the requested term will be made available *via* AgrO and thence in AgroFIMS, once verified.

AgrO is maintained using the OBO Foundry suite of tools [Ontology Development Kit[21] and ROBOT[22] (Jackson et al., 2019)] for the release process and with the Protégé tool (Noy and Mcguinness, 2001) for adding new terms. The ontology is openly maintained on GitHub,[23] allowing anyone to contribute. It is open source and available through several ontology registries including EBI-Ontology Lookup Service,[24] AgroPortal,[25] and Ontobee.[26] Although AgroFIMS was the first use case of the Agronomy Ontology, its continued growth and maintenance ensures wider relevance (e.g., to the agroforestry sector), and greater interoperability with existing standards in the life sciences. Annotations can be used to guide data entry in a database or when publishing to a data repository. As already mentioned, reliance on ontologies means that humans and machines understand the meaning behind data produced during an experiment designed using AgroFIMS. Thus, by relying on community standards to enable rich metadata and widely interpretable data, the tool generates data that is FAIRer than it would otherwise be and that requires minimal metadata cleaning before the use and publication of datasets.

RESULTS

AgroFIMS is conceived to be intuitive for agronomists through its alignment with typical operations involved in running an agronomic experiment and the use of terms that are part of the agronomist's research vocabulary, rather than the underlying semantic schema of its ontologies. The tool is organized internally in three modules as indicated in **Figure 2**: metadata, design and protocol, and variables.

AgroFIMS helps produce interoperable and findable data by tying data variables and metadata to industry standards

[17]https://github.com/AGROFIMS/ragapi.
[18]https://bigdata.cgiar.org/resources/agronomy-ontology/
[19]http://www.obofoundry.org/principles/fp-000-summary.html
[20]http://www.obofoundry.org/ontology/uo.html
[21]https://github.com/INCATools/ontology-development-kit
[22]http://robot.obolibrary.org/
[23]https://github.com/AgriculturalSemantics/agro
[24]https://www.ebi.ac.uk/ols/index
[25]http://agroportal.lirmm.fr/
[26]http://www.ontobee.org/

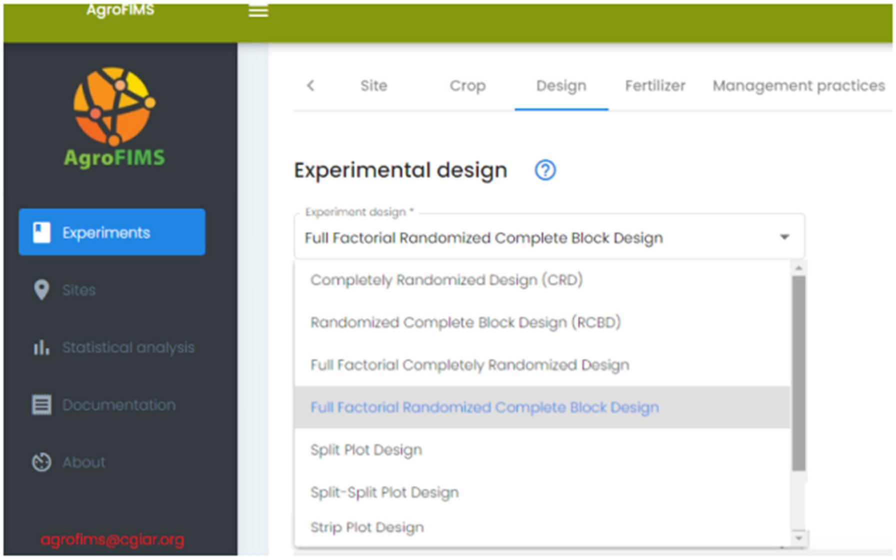

FIGURE 5 | Selection of experimental design choices currently available in AgroFIMS.

TABLE 1 | AgrAPI calls per category.

Category	Description	Number of calls
Experiment details	Provides the main metadata about the setup of experiment such as personnel, project lead and funding agency.	5
Site details	Provides the site and location information of the experiment. One experiment can include multiple sites.	3
Crop	Provides crop or group of crops of the experiment. Group of crops are allowed in intercrop and rotational experiments.	1
Design	Provides the experimental design layout of the experiment.	3
Fertilizer	Provide the fertilizer variables—fertilizer and nutrients elements—evaluated in the experiment.	1
Management practices	Provides agronomic management variables.	1
Field measurements	Provides crop and phenology variables.	2
Environmental variables	Provides weather and soil variables of the experiment.	2

for increased discoverability and interoperability such as the Dublin Core Metadata schema, the Agronomy Ontology, and the Unit Ontology. These are community-developed and agreed standards. Through the Platform for Big Data in Agriculture mediated efforts across the 15 CGIAR Centers, it is clear that the biggest hurdle to data FAIRification tends to be interoperability. We are addressing this challenge in the agronomy domain by linking data to ontology terms through AgroFIMS to make it interoperable, with great benefits for data curation, analysis and storage, thanks to the URIs associated with each ontology term. Additional benefits include rich data and metadata annotations, more data accuracy and reliability due to digital collection and in-built on-site validation, and increased interpretability by both humans and machines.

A concrete example of the advantages conferred by the ontology capabilities of AgroFIMS follows. The term "urea" which is part of the Agronomy Ontology is associated with the URI: http://purl.obolibrary.org/obo/CHEBI_16199 rendering it understandable to a machine and to a human. Further, because this term is part of an ontology, its relationships with other associated terms are inherited, allowing what is known as "inferencing." This means that users keying in "fertilizer" in a search engine will find this dataset even if it does not reference the term "fertilizer" because the ontology relationships specify that "urea" belongs to a class of things called "fertilizer." That is, the machine is able to infer through the ontology that urea is a fertilizer, rendering that dataset more easily findable and interoperable. Regarding the access and reuse concerns of FAIR, AgroFIMS recommends that data authors make their datasets as open as possible. However, the tool does not manage the accessibility of data or mandate licenses. This entirely depends on data authors and the particular policies or regulations they are governed by, but AgroFIMS is being developed to make it easier for data authors to choose appropriate open licenses

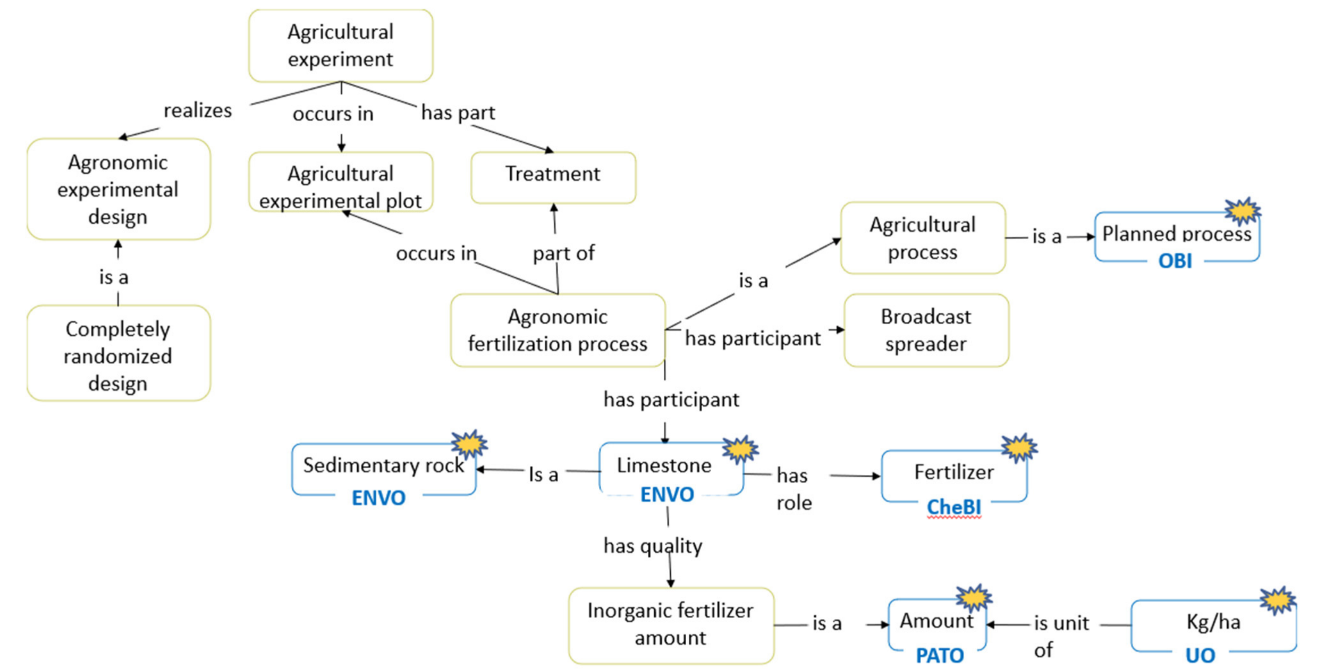

FIGURE 6 | A small part of the Agronomy Ontology, showing key relationships and hierarchies, and reliance on terms from other ontologies (asterisked, and in blue).

and check FAIR assets against actionable FAIR metrics, as already mentioned.

Apart from the value addition of born-FAIRer data recognized by the agronomist, crop modeler, and developer participants of user testing workshops at different phases of development, feedback has been positive concerning the user interface and navigation, and features including the provision of statistical scripts and analysis reports, direct upload from the AgroFIMS database to a variety of repositories, and plans to provide users with authoritative picklists (e.g., institution names from the Research Organization Repository or ROR[27] database). Some illustrative examples of efforts to enhance usability of AgroFIMS follow:

Crop measurements. Crop measurements listed in AgroFIMS are displayed depending on the crop selected earlier in the workflow. Thus, parameters such as "marketable yield" will be available as measurement choices for root and tuber crops, but not for cereals. Users can currently choose from 21 crops, including CGIAR mandate crops. If the crop used in the experiment is not listed, users may add one in a text field, and will then see a selection of standard measurements when specifying these.

Experimental design. Seven experimental designs are currently available in AgroFIMS. Once a design is selected, the treatment description is adapted to the number of repetitions or blocks, and AgroFIMS randomizes treatments, assigning plots to these.

Fertilizer calculation. Based on user feedback from workshops, a fertilizer tab was designed to support users in managing nutrient additions and determining the quantity of fertilizer or nutrient to apply in the field. The tab provides a calculation tool to either determine the quantity of fertilizer to apply or the quantity of nutrient that will be added to the field. This feature aims to reduce time and calculation errors by quickly providing users with the right amount of fertilizer or nutrient required in their trial.

To calculate fertilizer *via* this tool, users select if they are specifying a fertilizer product amount (e.g., diammonium phosphate, as illustrated in **Figure 7**) or nutrient amount (e.g., N, P, K). If fertilizer is selected, users choose from among a list of about 130 pre-registered products. For each product chosen, the system auto-loads nutrient content in the product (e.g., 18.0 and 20.1% N and P for standard diammonium phosphate); however, this content can be updated to fit a particular product blend, if different from the standard. Then users indicate the amount of fertilizer they wish to apply and the number of splits or applications (e.g., 2 applications each of 20 kg/ha and 30 kg/ha for the treatments specified in **Figure 7**). The timing, technique, and method of application can also be indicated, and the amount of nutrient calculated *via* an R script initiated *via* the "calculate" button (**Figure 7**). If nutrient is selected rather than product, users indicate the nutrient amount they want to apply (e.g., 40 kg/ha N; 20 kg/ha P; 10kg/ha K etc.) and select the fertilizer products. The tool then calculates the quantity of fertilizer to needed to deliver the desired nutrient amount.

Statistical analysis. Once data has been collected, those using the KDSmart application have the option to export their data and download them to the statistical analysis module of AgroFIMS. The module provides a statistical report of the data through

[27]https://ror.org/

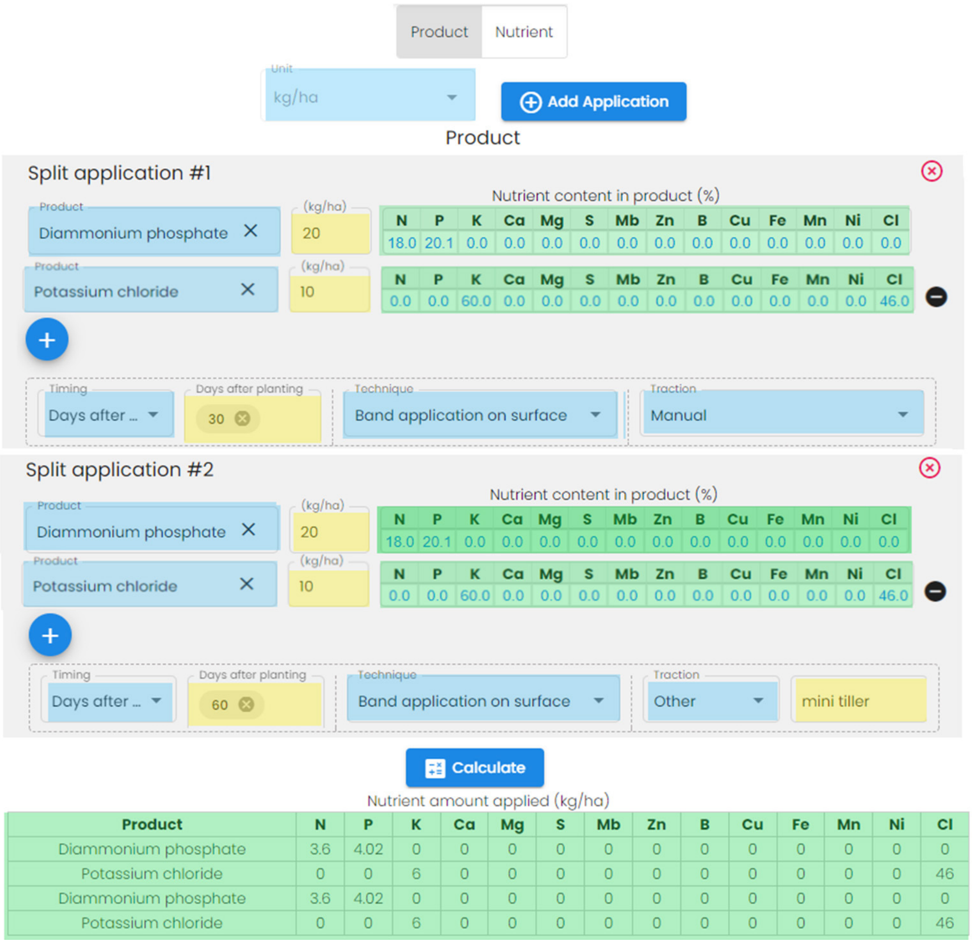

FIGURE 7 | Fertilizer pop-up window, showing system-generated information (light green); standardized choices (light blue); and user-entered text (pale yellow).

R scripts to assess such measures as the analysis of variances (ANOVA), Least Significant Difference (LSD) and Tukey tests. This provides a quick view of trial results and a validity check of the data, and a report that can be used in publications if needed.

DISCUSSION

In this paper we have presented AgroFIMS, an online tool allowing users to design agronomic trials through an intuitive user interface and to collect standardized data that eases aggregation and analysis. To these ends, AgroFIMS integrates the Agronomy Ontology and aligns metadata with ontology and other standards, ensuring more interoperable and findable agronomic data at collection. In order to design a demand-driven tool, user workshops and demonstrations were organized at various stages in the development of AgroFIMS. Feedback from potential users has highlighted the advantages and the limits of the tool, allowing its continuous improvement.

The key advantage acknowledged through user feedback is the ability to harmonize data collected through fieldbooks with standardized variables and parameters across projects and organizations, reducing data cleaning and processing time and allowing easier data sharing, aggregation, and reuse. The digital collection of data is also recognized as an advantage because this reduces human error and time for data to be available for analysis—and allows quick field validation and correction if needed. Therefore, the potential advantage of a tool like AgroFIMS is not just to the data (re)user, but to the data generator as well. Projects can be large multi-locational endeavors, operational in many locations within a country or many countries. Different data collectors are often tasked with data collection, and no matter how stringent the data collection templates, and data collectors' trainings, collected data is typically inconsistent (in terms of data variable names, methodologies used to manage aspects of field trials, units, and more). In instances where digital data collection is not used the data can have errors, which are often only noticed days, weeks or months after the data has been collected, making it virtually impossible to revisit and/or redo the measurement. This means that the project manager and others associated with the project must spend more time and effort than necessary to standardize data for their own analyses and meta-analyses—when they could instead use a tool that enables digital collection of standardized data in trials subject to relatively standard management and data collection methodology (*via* protocols bundled into the data collection tool). Another advantage of a tool like AgroFIMS is that coding skills are often necessary to use and set up electronic collection tools. Using AgroFIMS, any scientist can go through user-friendly web interfaces to set up their experiments and load the AgroFIMS output directly into mobile collection apps, such as KDSmart.

In recent years, digital data collection tools are gaining prominence in agricultural research. These tools usually provide some statistical analysis capabilities, which are important for scientists and save them time. Such tools exist primarily in the plant breeding world, with notable examples being the Breeding Management System[28] of the Integrated Breeding Platform and the BreedBase[29] system developed by the Boyce Thompson Institute. These approaches focus on standardizing plant phenotype data with links to ontologies such as the Crop Ontology, but management practices are often not standardized or shared. Further, breeding experiments follow experimental designs that are generally simpler than in agronomic experiments, usually involving one unique treatment with several factors, and using only the crop genetic material as an entry point. In contrast, agronomy trials are concerned with a large variety of management practices and treatments, much less so with the germplasm.

Other examples of digital data collection in the agricultural domain are ClimMob[30] which facilitates the design of agricultural citizen science experiments, and RhoMIS, for the creation of household surveys (Hammond et al., 2017). These tools are based on ODK forms, where users create questions that are recorded in the fields. These tools embed a set of recommended questions in pursuit of standardization, but the data generated are not necessarily standardized, which is a barrier to its reuse. These limitations led us to developing an approach which focuses on standardizing data from the start, taking into consideration experimental design, including treatments and management practices, and crop phenotype data.

Despite the advantages of AgroFIMS, there remain cultural and technical issues to its adoption, the former of which is the more difficult to address. Using the tool requires users to change how they are used to collecting data, often with large numbers of partners trained to do so in particular ways. In addition, the pre-filled lists are based on standard vocabularies that employ commonly used terms, measures, and their synonyms. However, this harmonization is complex as some measures may have many names; a measure may therefore be missing or be represented by a name other than the one most often used by the user, which can be frustrating.

From the technical standpoint, at least one important agronomic concept has not yet been tackled: While AgroFIMS covers a season with one or more crops as monocrop or intercrop systems, the complexity of long-term rotation experiments is still being conceptualized and developed. AgroFIMS works for controlled trials such as those occurring on agricultural experiment stations, with well-defined and replicated designs. Further, trials implemented by CGIAR scientists are increasingly on farmer fields, with hundreds of farmers, in sites for which location information is unknown prior to data collection. The current version of AgroFIMS cannot accommodate this, as its workflow begins with site specification. Some or several aspects of these trials may be managed by farmers, and data may be collected by enumerators who question farmers on their management practices and are responsible for several tens or more of farmers.

Development efforts for 2021 are therefore focused on exploring the development of ODK forms with key parts of questions or instructions recognized by built-in semantic engines to be part of an ontology. These engines will enable links to proposed ontology terms and URIs that a human can verify. That is, for the question: "Has *cassava* been grown in the past in this *field* as a *monocrop*?" the tool will recognize the standardizable terms of the question (the words in italics), and link these to the correct ontology terms. Through these direct links to data standards, the generated ODK forms and fieldbook will therefore begin to enable standardization of datasets.

The goal for the next version of AgroFIMS is to overcome such current limitations and offer a solution that more fully supports data management. The vision for this improved tool includes data collection that can handle data collection from different agronomic trial types; pipelines to the FAIR workflow currently in alpha version to strengthen user ability to easily address aspects of data accessibilty and reuse, a database integrated with CGIAR's collaborative analytical CG Labs[31] environment built on Jupyter notebooks for teams to work together on data processing; access rights and roles at project level; and the possibility to push data to repositories and the GARDIAN discovery portal once project teams are ready to do so. Team members and enumerators will access data collection forms *via* CG Labs or other sharing platforms, with the goal of ultimately providing access through a single database. Once data is collected by enumerators, they will be able to upload the forms back to CG Labs or any ODK-compliant platform that offers an API for data to be pulled/synced into CG Labs (e.g., ONA[32]). CG Labs provides easy access to Git repositories, R libraries, crop model pipelines (e.g., WOFOST, Ecocrop, DSSAT), and a large number of data services, including very large (7-10 TB) datasets. This environment therefore makes it easy to clean, process, and analyze data with other team members, interoperating at the same time with other datasets of relevance.

[28]https://www.integratedbreeding.net/
[29]https://breedbase.org/about
[30]https://climmob.net/blog
[31]https://gardian.bigdata.cgiar.org/labs.php
[32]https://company.ona.io

An infrastructure is therefore envisaged by 2022 that allows researchers to design survey forms and fieldbooks, share these with enumerators, and frequently upload and assess the data collected. It will facilitate easy aggregation, processing, analysis and saving of the final dataset to a global database, also allowing easy uploads of well-annotated, interoperable datasets to an institutional or global repository.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

MD conceived the idea based on a data dictionary she developed for her research. OB and IP developed the AgroFIMS backend and user interface. MD and CA established the content of the tool and organized user testing workshops. MA-L investigated linkages with ontologies. M-AL and CA added terms used by the tool to relevant ontologies. All authors brainstormed to help conceptualize key features, navigation, UI, other elements of the tool, and contributed to the final manuscript.

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frontiers in Sustainable Food Systems

SYSTEMATIC REVIEW
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What's Stopping Knowledge Synthesis? A Systematic Review of Recent Practices in Research on Smallholder Diversity

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A systematic review of recent publications was conducted to assess the extent to which contemporary micro-level research on smallholders facilitates data re-use and knowledge synthesis. Following PRISMA standards for systematic review, 1,182 articles were identified (published between 2018 and 2020), and 261 articles were selected for review in full. The themes investigated were: (i) data management, including data source, variables collected, granularity, and availability of the data; (ii) the statistical methods used, including analytical approach and reproducibility; and (iii) the interpretation of results, including the scope and objectives of the study, development issues addressed, scale of recommendations made relative to the scale of the sample, and the audience for recommendations. It was observed that household surveys were the most common data source and tended to be representative at the local (community) level. There was little harmonization of the variables collected between studies. Over three quarters of the studies (77%) drew on data which was not in the public domain, 14% published newly open data, and 9% drew on datasets which were already open. Other than descriptive statistics, linear and logistic regression methods were the most common analytical method used (64% of articles). In the vast majority of those articles, regression was used as an explanatory tool, as opposed to a predictive tool. More than half of the articles (59%) made claims or recommendations which extended beyond the coverage of their datasets. In combination these two common practices may lead to erroneous understanding: the tendency to rely upon simple regressions to explain context-specific and complex associations; and the tendency to generalize beyond the remit of the data collected. We make four key recommendations: (1) increased data sharing and variable harmonization would enable data to be re-used between studies; (2) providing detailed meta-data on sampling frames and study-context would enable more powerful meta-analyses; (3) methodological openness and predictive modeling could help test the transferability of approaches; (4) more precise language in study conclusions could help decision makers understand the relevance of findings for policy planning. Following these practices could leverage greater benefits from the substantial investment already made in data collection on smallholder farms.

Keywords: agricultural research, best practices, systematic review, quantitative research, smallholder agriculture

INTRODUCTION

Growth in agricultural GDP has been shown to especially benefit the poorest members of society (Ligon and Sadoulet, 2008). Rural areas account for 54% of the world's population, but 79% of the total poor. Agricultural workers accounted for two thirds of the world's extreme poor. Smallholder farms (those of <2 hectares in size) make up 84% of the farms worldwide (Lowder et al., 2016). Agricultural development interventions are an important driver of poverty reduction and smallholders, the targets of these interventions, have even been labeled the "backbone" for implementing the SDGs (Terlau et al., 2019).

Rural development interventions aim to improve the quality of life for smallholders through increases in agricultural productivity, or other dimensions such as improved food security and human well-being. Agricultural research for development is essential for improving the delivery and targeting of development interventions. Traditionally, these interventions were tested in a controlled environment (Wigboldus et al., 2016). Once proven to be effective, they were then made available at a large scale. The uptake of interventions was generally driven by social networks and material incentives and the benefits of scaling exercises were usually assumed rather than measured. This scaling pattern can be thought of as linear, following three key stages: (1) "Find out what works"; (2) "Cross the divide through extension, transfer, diffusion and/or adoption"; (3) "Do more of the same."

In recent years, there have been important changes to advice on how development interventions are designed, delivered, and studied. Research has shown that some demographic groups benefit more than others from particular interventions, both in terms of adoption and impact (Hammond et al., 2020). Researchers are now investigating how interventions can be tailored to work best for particular demographic groups, and how they can effectively "scale-up." The PRactice-Oriented Multi-level perspective on Innovation and Scaling (PROMIS) calls for an iterative approach to scaling (Wigboldus et al., 2016). Instead of only testing interventions in a controlled environment, the PROMIS framework states that development practitioners should consider the impact of interventions as they become available to new demographic groups and in new locations. The PROMIS framework also calls for more research into the multiple scales at which we need to consider impact and determinants of adoption. For example, contextual factors, such as climate, local infrastructure, and access to markets can also influence the uptake and impact of an intervention. These multi-level interactions are rarely considered (van Wijk, 2014).

Understanding the dynamics of agricultural development processes for different demographic groups requires large amounts of household-level data. Synthesizing knowledge from this data is the key challenge we address in this manuscript. Traditionally, narrative reviews were used for knowledge synthesis, however these are often not useful for summarizing complex findings across a large numbers of studies (Gurevitch et al., 2018). Instead, meta-analyses are generally used where large numbers of studies exist across a range of contexts. These analyses come in two main forms: (1) aggregated meta-analyses, which examine results of multiple studies; (2) meta-analysis of individual participant data, which compiles the primary data of multiple studies for combined analysis (Eisenhauer, 2021). In aggregated meta-analysis, the focus is on study findings, the compatibility of the samples, and the methods used to generate these findings. In meta-analysis of individual participant data, considered a gold standard, information on the study design, data-sources, variable selection procedures, and heterogeneity between studies are all required (Riley et al., 2010). For either type of meta-analysis to be reliable, structured information on study design, the data-collected, the methods used to analyze these data, and a clear presentation of study findings, are all essential.

There are several practices in rural development research which make it difficult to conduct this type of collaborative data-driven research at multiple scales: rural development research is highly multi-disciplinary; the interventions evaluated, the metrics used to monitor impact, and the methods used for analysis are incredibly diverse (Carletto et al., 2013); high quality agricultural data, and particularly high-quality smallholder household surveys, are rare due to issues with recall and harmonization (Carletto et al., 2015; Fraval et al., 2019). Studies which took place across different times, locations, and scales require thorough contextual descriptions in order to understand the role of environmental and socio-economic context in influencing outcomes.

In recent years, there have been vast improvements in the availability of data, the efficiency of data-collection tools and the methods used to link and analyze these data. Micro-level research on smallholders, which has been hampered by a lack of data, can now capitalize on these advancements. There is a growing body of literature on data-driven methods to understand smallholder farms in relation to rural development objectives. Concurrently, best practice guidelines for data-intensive research have evolved and gained more prominence. In light of recent advances, we assess the degree to which recent micro-level research on smallholders is aligned to best practice principles, for example, the FAIR principles, the Turing Way, and the STROBE guidelines (von Elm et al., 2007; Wilkinson et al., 2016; The Turing Way Community et al., 2019). Finally, we identify gaps/opportunities where conforming to these best practices could increase the impact of micro-level smallholder research for development impact, and lead to a more collaborative research system centered around data re-use and generation of more useful, scalable insights.

The research question we address in this article is:

1. *To what extent do current research practices facilitate the re-use of data and the synthesis of knowledge?*

We identify three objectives in relation to this goal:

1. *Review and characterize recent quantitative approaches which aim to understand smallholders and inform development practice.*
2. *Assess the degree to which best practices in data collection, data management, data analysis, and interpretation have been taken up in research on smallholder farmers.*
3. *Make recommendations for best practice which could be applied to add value to ongoing work in this field.*

TABLE 1 | The inclusion and exclusion criteria used to identify relevant articles during the title-abstract review and the review of full articles.

Inclusion criteria	Exclusion criteria
The article draws on structured survey or other closed data-collection methods (i.e., is not solely qualitative).	Articles solely using unstructured survey methods or focus groups.
At least one data source had to be meaningful at the household level.	The article was a review or was solely theory based, all data used was at field level, or all data was aggregated above household level.
The article used/analyzed/produced data that considers the heterogeneity of smallholder farmers.	The article did not consider how the findings/predictions vary for different farms (such as those with different resource endowments).

METHOD

Our approach followed the PRISMA standards for a systematic review (Moher et al., 2009). The following steps were undertaken: (a) we identified a suitable database which can be used to identify potentially relevant articles; (b) we developed a search string to articles relevant to the research question; (c) we screened the articles based on title and abstract using clearly defined inclusion/exclusion criteria; (d) we used a set of predefined criteria to extract information from reviews of full articles.

Article Identification

We only examined academic research in this review. We considered *Scopus, Web of Science,* and *Google Scholar* as search engines to identify relevant articles. *Scopus* outperformed *Web of Science* in most disciplines (Martín-Martín et al., 2018), and while *Google Scholar* had the widest coverage, many of the articles were non-academic and contained few citations. Therefore *Scopus* was chosen as the most suitable database.

There is no widely accepted heuristic for determining sample size for this type of review. We considered three important points: (i) the review should represent the most contemporary research practice, (ii) the sample of articles should be sufficiently large to identify common practices, and (iii) it should be small enough to conduct the review in a realistic time frame. A similar systematic review, focusing on best practices in the biomedical literature, examined 149 articles published between 2015–2017 (Wallach et al., 2018). Like Wallach et al. (2018), we determined that examining research over the past two years would provide sufficient representation of the field, whilst not overly skewing results with the less up-to-date practices of older research efforts. Guidelines for best practices in data-intensive research have gained traction in recent years, and we wanted to review articles which had been published after some of these guidelines. Examples of such best practice guidelines include: the FAIR principles (Wilkinson et al., 2016); the Turing Way (The Turing Way Community et al., 2019); the OECDs recommendations for access to research data (OECD, 2021); the Transparency and Openness Promotion Guidelines (Nosek et al., 2015).

Based on this approach, a general search of all articles (2018–2020) containing "smallholder," or any variants of it, was conducted. This resulted in 2,788 articles. To further focus the review, we narrowed the search to articles focused on rural development. To do this, the common keywords which featured in the 2,788 articles were analyzed. We identified the keywords aligning with rural development objectives (e.g., productivity, sustainability, climate change, poverty, and health) and used these to develop the final, and more targeted, search string. The final search string, and the keywords from these articles can be found in the **Supplementary Materials**.

Title Abstract Review

Once all articles for review had been identified, the most relevant were selected through examination of their titles and abstracts, and comparison against a set of inclusion and exclusion criteria (**Table 1**). All these inclusion criteria had to be met and none of the exclusion criteria for an article to pass through to the next stage. The criteria were:

1. Only articles which included quantitative data were selected (i.e. purely qualitative studies were excluded, as this type of data is less suitable for re-use, harmonization, and meta-analysis across multiple studies);
2. Articles must use data which considers the heterogeneity of smallholders (i.e. the data should be sufficiently granular to allow identification of differences between smallholders within a single study);
3. At least one data source must be meaningful at the household level (i.e. fit the definition of micro-level research, or linking between the micro-level and other levels).

Full Article Evaluation

Selected articles were then reviewed in full. After reading the full article, each was re-assessed using the initial inclusion-exclusion criteria from the title abstract review to ensure they were indeed eligible. Then each article was evaluated using a further, predefined set of criteria. These additional, more detailed criteria were designed to evaluate whether the research was conducted in a manner to facilitate data re-use and knowledge synthesis. These criteria were informed by the requirements for an article to be suitable for meta-analysis, meaning an article must include information on: the study design; the data collected; the methods used to analyze these data; and the interpretation of

TABLE 2 | The criteria used to evaluate full articles.

Category	Variable	Description of variable
Data creation and management	Data source	The original source of the data used in the article. This could include the method of data collection (e.g., surveys) or the method used to source the data (e.g., data generated from modeling exercises).
	Level of data	The level at which the information is relevant. For example, soil samples are relevant at the field level, surveys at the household level, and aggregated statistics at the community level.
	Spatial coverage of the dataset	The geographic area covered by the data points.
	Countries covered	Countries included in the dataset.
	Description of study site present	Many articles include a description of the study site, with key information about topography, climate, and the main crops cultivated. This documents how this information was recorded (e.g., supplementary material, in the manuscript).
	Sample size	The number of data points collected at the household level.
	Data availability	The availability of the data used in the study.
	Longitudinal data used	Whether or not longitudinal data was used in the article being studied.
	Data documentation	How data, which has been made public, is documented for new users.
	GPS recorded	Whether or not GPS was recorded in the study.
	Multiple data sources linked	Whether the data sources (e.g., household surveys) were linked to other forms of data (e.g., satellite imagery or climate data).
	Household level variables recorded	What measures were collected at the household level (e.g., education level, household size, annual income). For meaningful interpretation, household variables were grouped by topic, even if the precise measurement method or question differed.
Analysis methods	Methods type	The methods used (e.g., clustering methods, linear regression, descriptive statistics).
	Purpose of regression	Where regression was used, we documented how it was conducted and the ultimate purpose of the regression (e.g., interpreting associations between variables, predicting new information, inferring causal relationships).
	Methods availability	Were the methods made available? Where scripted analysis tools were used, were the scripts easily accessible? Where graphical user interface tools (e.g., Excel) were used, was any material shared that could help reproduce the findings?
	Methods documented	Where methods were shared, did the authors include documentation along with the methods?
	Software used	What software was used to conduct the analysis (e.g., excel, SPSS, R, python)?
Interpretation	Development objectives targeted	Which general themes were addressed by the article?
	General policy recommendation	Was a general recommendation made that was targeted at policy makers?
	Recommendation for farming management	Were recommendations made for changes at the farm level?
	Recommendation for future research	Were recommendations made on how future research should be conducted?
	Type of recommendation	Did the recommendation focus on farm-level variables, or did they focus on the farmer's context? (e.g., local infrastructure).
	Spatial scale of recommendations	What was the scale of the recommendations? Based on the authors' language, were findings attributed to smallholders in the area studied, to areas with similar characteristics, or to smallholders in general?
	Tools produced	Were any tools produced in relation to the research, such as modeling software or decision support tools?

findings. The criteria, and the options used for each criterion are presented in full in **Appendix A.1**, and summarized in **Table 2**. All analysis was conducted using the programming language (R Core Team, 2021).

RESULTS

Article Selection and Screening Process

The article selection and screening process is summarized in **Figure 1**. During the initial broad search 2,788 articles were identified which contained the word smallholder, or any variant of it. The search string was refined, using the steps outlined in Article identification. The refined search string was used to identify 1,182 remaining articles. During the title and abstract screening phase, 884 articles were excluded. Most of the articles which were excluded (60%) were excluded because they did not consider the differences between smallholders within the study (most looked at a single household variable only). A fifth of articles did not meet any of the inclusion criteria. While remote sensing can be used to add detailed information to studies, 72% of the articles which included remote sensing data had to be excluded because they did not combine it with data at the household level. The total number of articles thus selected for review was 298. During full review, a further 37 articles were excluded as on closer examination they did not use any quantitative data.

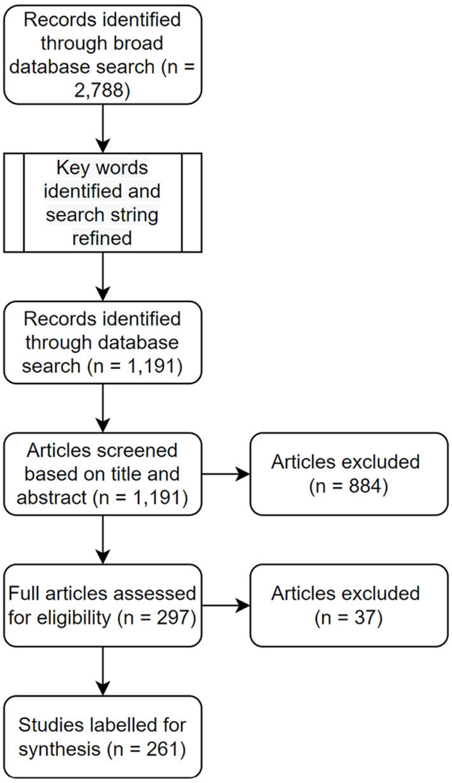

FIGURE 1 | PRISMA diagram illustrating the article selection process.

Description of Final Articles Selected

In total, 261 articles were reviewed in full, 49% of these were open access. A dataset containing the full list of articles reviewed, their associated meta-data, and how they were labeled can be found in the **Supplementary Materials**. The reviewed articles came from 127 journals. The 10 most common journals were: *Sustainability* (23 papers), *Agricultural Systems* (13 papers), *World Development* (13 papers), *Food Security* (12 papers), *Journal of Rural Studies* (12 papers), *Land Use Policy* (12 papers), *PLoS ONE* (8 papers), *Climate and Development* (7 papers), *Agriculture, Ecosystems and Environment* (6 papers), and *Food Policy* (6 papers). Many of the papers did not specify their funding sources. The three most frequently cited sources were USAID, the Bill and Melinda Gates Foundation, and the UK Department for International Development (DFID, now part of the Foreign, Commonwealth & Development Office). The articles reviewed studied a wide variety of locations, with the most frequently studied countries being Ethiopia (18%), Kenya (13%), Ghana (10%), Uganda (9%), Tanzania (8%), and Nigeria (5%).

The main development objectives addressed in the articles were climate change and adaptation (25%), agricultural productivity and efficiency (17%), and adoption and scaling of interventions (16%). Other topics which occurred less frequently included perceptions and decision making (13%), gender (12%), livelihood and food sourcing strategy (11%), nutrition (10%), food security (10%), health (10%), farm practices and management (10%), sustainability and environment (10%), vulnerability and resilience (7%), local infrastructure, laws, and services (5%), methodology (5%), and welfare and social issues (5%).

TABLE 3 | A summary of the data used in articles examined during the full article review (*N* = 261).

Variable	Option	Percentage occurrence
Data collection method	Structured surveys	95%
	Qualitative	26%
	Remote sensing	10%
	Aggregated statistics	7%
	Semi-structured survey	7%
	Other	2%
Granularity of data	Household	100%
	Local (community) level	11%
	Sub household	9%
	Other	5%
Level at which data was representative	Sub-national	48%
	Local/Community	31%
	National	11%
	Unclear	8%
	Other	3%
Longitudinal data used	No	86%
	Yes	14%
GPS data collected	Unspecified	80%
	Yes	15%
	No	5%
Data linked to other datasets	Yes	19%
Data availability	Data closed/private	77%
	Data newly made open	14%
	Data already public	9%
Data documented	Data not made available	76%
	Data documented	15%
	Unclear	8%

Data Creation and Management

Table 3 summarizes data creation and management findings, showing that structured surveys were the main method of data collection, featuring in 95% of articles reviewed. Other data sources were generally used to supplement the findings from structured surveys. For example, qualitative data, including focus group discussions and open-ended interviews featured in 26% of the articles. Often, quotes from focus-group discussions were used to support statistical findings from the survey data. Other data sources appeared less frequently: remote sensing data was used in 10% of articles; aggregated statistics, such as averages at the county level were included in 7% of articles; crowd-sourced data sources, mobile-phone records and other sources of data appeared in only a few articles.

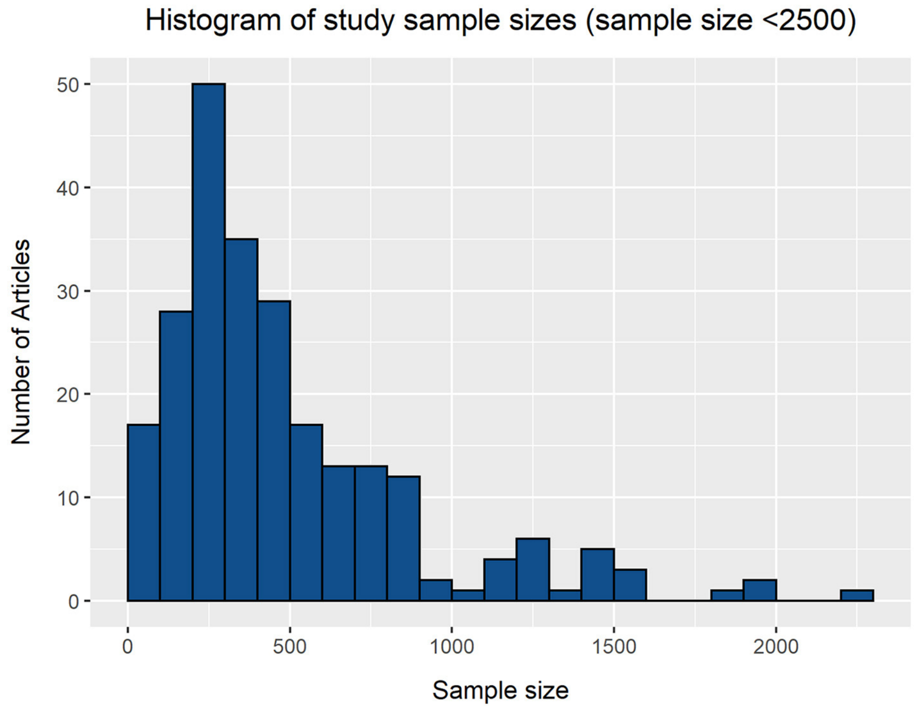

FIGURE 2 | Histogram showing the distribution of sample size, for household level data, across the articles reviewed. Only articles with a sample size of <2,500 are presented. There were 16 articles with a sample size >2,500, ranging from 2,710 to 8,938.

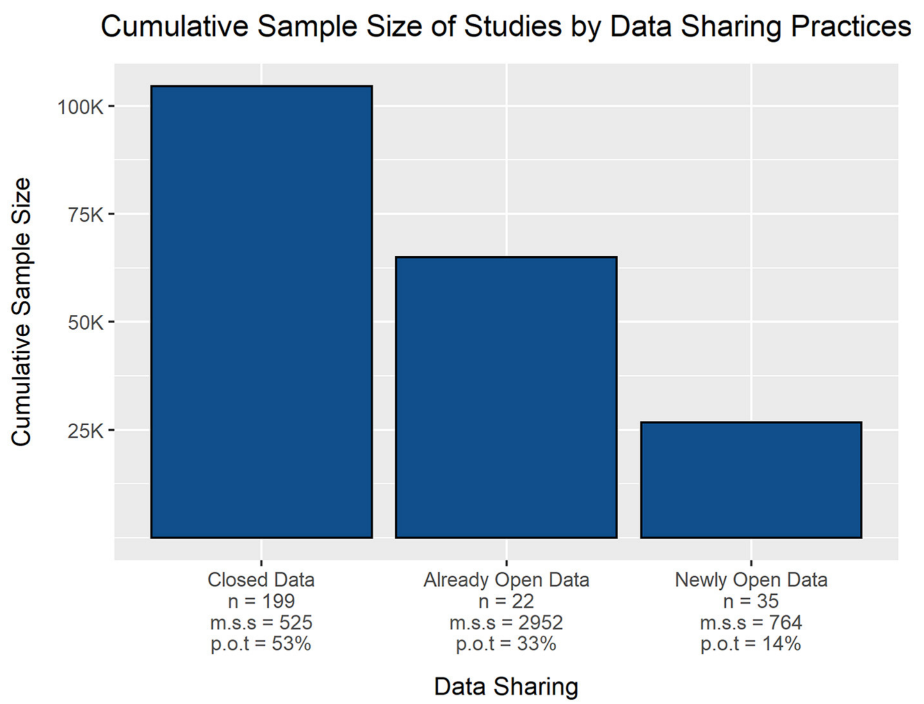

FIGURE 3 | A barchart showing the cumulative sample size of household-level datasets used by articles, disaggregated by data-sharing practice. Number of articles is represented by "n," mean sample size represented by "m.s.s," and percentage of total samples collected represented by "p.o.t".

TABLE 4 | Summary of the themes covered by articles and the key variables that they examined.

Category of variable collected	Percentage of articles containing at least one measure	Number of measures	Measures
Household	83%	10	Education (70%), age (65%), household size (58%), experience in farming (24%), marital status (16%), ethnicity (8%), constructions materials for house (7%)
Farm characteristics	79%	9	Land size (69%), livestock holdings (38%), crop diversity (20%), land tenure (19%), land allocation (18%), land fragmentation (8%)
Economic	77%	18	Total income (29%), crop income (25%), assets (23%), livelihood strategies (20%), off farm income (18%), livestock income (18%), off farm engagement (16%), wealth indicator (10%), consumption (9%), general expenditure (8%), remittances (7%), savings (5%)
Access	77%	14	Access to credit (36%), group membership (31%), access to markets (30%), access to extension services (30%), access to irrigation (21%), access to information (15%), training (10%), access to roads (8%)
Gender	59%	2	Gender of household head (58%), gendered control (6%)
Farm management	51%	8	Farm management (38%), labor (33%), yield (26%), equipment owned used (11%)
Contextual	33%	9	Climate (17%), soil (11%), topography (7%), agroecology (5%)
Perceptions and knowledge	26%	4	Perceptions (25%), other (3%)
Food security	16%	2	Food security (11%), nutrition (9%)
Other variables	11%	9	Social capital (10%), Health (8%), Mobile phone use (5%)

Variables which occurred in <5% of articles are excluded.

In addition to collecting household-level information, some studies combined this with data of a different granularity. For example, information such as household size and household income was considered to be at the household level, but assessment of the average age of people within a village could be considered to be at the "local/community" level. It was observed that data relevant at the landscape level was combined with household level data in 11% of articles, this included aggregated information on local physical geography or socioeconomic characteristics. Data which was relevant below the household level, such as information on individual fields, appeared in 9% of articles. Other levels of data, such as sub-national or national data, were rarely included in analyses.

The spatial coverage of the datasets ranged widely. Smaller-scale studies were much more common than larger-scale studies. Datasets with sub-national coverage (i.e., with samples across an entire county) featured in 48% of studies reviewed. Landscape-level studies, which drew on samples from a few clustered villages, featured in 31% of studies. National-level studies, with data covering the majority of subnational units, featured in 11% of the articles reviewed. International-level studies, which either focused on whole regions (e.g., East Africa), or were multi-continental, were extremely rare. In 8% of articles it was not possible to estimate the spatial coverage of the datasets. In most cases, articles were not explicit about the statistical representivity of their datasets. So, while their coverage may have been large, whether the findings were truly representative of the areas investigated was not clear.

None of the reviewed studies used more than one quantitative household-level dataset. The sample size of household-level datasets varied widely, the distribution of sample size is presented in **Figure 2**. Most studies had a sample size of <500 households. **Figure 3** summarizes cumulative sample size in relation to the public availability of the underlying data. Larger-scale studies generally drew upon publicly available datasets. Cumulatively, smaller studies which do not share their data accounted for the majority of household-level data points (104,521 households). New data, which was collected for the study and made publicly available accounted for 26,737 household-level data points. Publicly available datasets (e.g., World Bank LSMS-ISA; Osabohien, 2018) accounted for 64,945 household-level data points in the studies reviewed, although it is doubtful that these are all unique datapoints as public data-sets tended to be re-used.

Regarding data sharing and documentation, 77% of articles did not provide ways to make the data accessible. Documentation on the data used was included in 15% of articles, this includes the articles which drew on publicly available resources, where documentation was already available. In 8% of cases, it was unclear whether documentation had been provided, this was in cases where the data was available "upon request." In 2% of cases, articles shared their data and provided no documentation at all. Only 15% of articles explicitly mentioned the use of GPS coordinates to label their data spatially, facilitating linkage to other types of spatial datasets. Longitudinal (multiple time point) datasets were identified in only 14% of studies, even though many more articles were investigating processes which change over time, such as technology adoption or climate change adaptation.

Harmonization of Variables Collected

The articles reviewed contained a wide range of household-level measures. Measures often differed in how they were recorded during data collection. For example, in a survey "household size" can be determined through a household roster, or simply by asking for the total number of people in the household.

TABLE 5 | Analysis methods, replicability and software used.

Variable	Option	Occurrence
Method Type	Descriptive stats	93%
	Single level regression	64%
	PCA	17%
	Clustering	8%
	Stochastic frontier	5%
Use of regression	Association	71%
	Prediction	2%
	Causal analysis	Nil
	Regression not used	28%
Analysis methodology replicable	Described in manuscript	97%
	Code available online	3%
Software used for data analysis	Not specified	44%
	SPSS	19%
	stata	18%
	R	16%
	Other	8%

Methods appearing in <5% of articles not included.

In this review, these would be classed as the same "measure," recorded in two different ways. We identified 88 measures in total, summarized in **Table 4**. The most frequent measures used in the reviewed articles were education level of the household head (70%), land size (69%), household size (58%), and the gender of the household head (58%). Many measures did not appear very frequently. Despite differences in measures recorded, many articles collected information on a small number of common themes or topics. These themes are also summarized in **Table 4.** A total of nine themes were identified: household demographics (89% of articles contain at least one measure in this category), farm characteristics (87%), economic (79%), access to services and infrastructure (77%), farm management (62%), gender (61%), contextual features (33%), perceptions and knowledge (27%), and food security (16%).

Analysis Methods

The analysis methods used, and how these methods were used and shared, are summarized in **Table 5** (further details in **Supplementary Material**). The analyses of the reviewed articles predominantly relied on descriptive statistics and single-level linear or logistic regression, which appeared in 93% and 64% of articles respectively. More advanced machine-learning methods occurred much less frequently.

Best practices for reproducibility were also investigated. Although scripted analysis software, such as the *R programming language, python,* or *STATA* were used in a third of the articles reviewed, analysis scripts or workflows were only shared in 3% of the articles reviewed and only 2% of articles provided documentation for their analysis scripts. Approximately half of the articles reviewed did not specify the software they used to conduct their analyses.

Linear and Logistic Regression

The use of linear and logistic regressions to understand smallholder heterogeneity is widespread, and as such, it warrants special attention. In the articles reviewed, these regression approaches were used to infer relationships between independent and outcome variables. For example, many technology adoption studies used linear regression to understand the relationship between technology adoption and household characteristics (e.g., age and years in education). Simple linear and logistic regressions were used in 64% of studies. More complex types of regression were used much more rarely. These included multi-level modeling, Bayesian regression methods, and partial least squares (PLS) regression. In total, 72% of articles used at least one type of regression method. In 71% of all articles, regression was used for association purposes. In these cases, the regression parameters, along with the appropriate significance tests or uncertainties, were used to infer the strength of association. In 2% of articles, a fitted regression model was used to make predictions. Here, data was split into training data and test data, with accuracy of the model assessed based on how accurately the trained model could predict values in the test set.

Interpretation

The Types of Conclusions Drawn and Recommendations Made

Table 6 summarizes how data and results were interpreted in the articles under review. The intended audience for the recommendations was primarily policy makers, who were addressed in 84% of studies. Recommendations for future research were also common, featuring in 54% of articles. Recommendations about specific farming practices featured in 20% of articles.

Although there was a diverse range of recommendations proposed in these studies, they can broadly be conceptualized in two ways: creating an enabling environment (supra-household); and modification to household or household members' behavior (intra-household). These recommendation types were not mutually exclusive. Supra-household recommendations were made in 70% of articles. This was consistent across the different topics of the articles. These interventions included improvements to financial services, road quality, and information provision. Intra-household interventions were suggested by 36% of articles, which included changes in livelihood strategy, gendered decision making, and farmer-to-farmer information sharing. Other types of interventions, which were typically methodological improvements focused on researchers, were suggested by 15% of articles.

There was often a mismatch between the scale at which the recommendations were pitched vs. the scale at which the data was representative (**Table 6**). There were 208 articles where it was possible to determine the spatial coverage of the data, and the spatial coverage ascribed to the article's conclusions. Of these 208 articles, 59% drew conclusions with larger spatial coverage than their datasets. Over one third (38%) of articles drew general conclusions about smallholders in general, without reference to any specific locations or demographic groupings. Articles using local and subnational scale data more commonly drew

TABLE 6 | A summary of the types and scale of conclusions drawn, and the intended audience for the recommendations.

Variable	Option	Occurrence
Audience for recommendations	Policy	84%
	Farm management	20%
	Further research	54%
Farm level and/or contextual recommendations	Creation of enabling environment	70%
	Farm level changes	36%
	Other	15%
Recommendation scale	All smallholders in general	38%
	National	26%
	Sub-national	21%
	Local	11%
	Not relevant	10%
	Regional	5%
	Unclear	4%
	Areas with similar characteristics	3%
Representation of data matches the scale of recommendations made	Claim beyond data	59%
	Claim equal to data	22%
	Not possible to determine	19%
Tools produced	No	99%
	Software for analysis	1%

"general" conclusions compared to articles using larger-scale datasets. Only one quarter explicitly confined their conclusions to the area covered by their datasets. In 26% of articles, conclusions were made at the national level, attributing their findings to all smallholders within the country studied. In 21% of articles, conclusions were drawn at the sub-national level (the largest administrative unit below the national level). In 11% of articles conclusions were made at the local level (any area below sub-national). At the larger scale, regional and global conclusions were much less common, occurring in 5 and 2% of articles respectively. Finally, only 3% of articles explicitly stated that their conclusions were relevant to areas with similar physical geography and socioeconomic characteristics. **Table 7** compares the coverage of article data to the scale of the conclusions or recommendations made.

Description of Study Context and Enabling Environment

While all articles used household level data in their analysis, some articles also included contextual information in the analysis, and many reported contextual information even if it was not used in analysis. This includes information on local infrastructure, climate, and markets. We define context to be information which is unique to each farming system due to its physical location. In 96% of articles a description of the study site was included. For 90% of articles, these descriptions were a mixture of text and tables. For 6% of the articles reviewed, contextual information was also included as **Supplementary Material** that could be easily downloaded and analyzed. Studies generally followed a pattern of describing the climate, physical geography, common farm systems and crops grown, and occasionally details about local infrastructure and markets. As discussed in harmonization of variables collected contextual information was rarely included in the formal analysis. For example, although climate and topography featured in almost every site description, they were only used in 17% and 7% of analyses, respectively. Most (70%) articles discussed the need for interventions which impact farm context (e.g., better infrastructure). Of these articles, only 33% of actually included information about farm context in their analysis.

Key Findings

Table 8 summarizes the main findings, showing that more articles tend to be located at the finer spatial scales, drawing on data which has local or subnational coverage. These smaller-scale datasets are rarely made open access. Descriptive statistics are used in almost all the smaller-scale articles, and single-level linear or logistic regressions are used in the majority. Smaller-scale studies in general make claims which extend beyond the coverage of their datasets in most cases. National and international-level studies which draw on household-level data are much rarer. For these larger-scale studies, publicly available datasets are used much more frequently. Where larger-scale new data is collected, it is more often shared. In the majority of cases, large-scale studies make claims which match the scale of their datasets. Across all scales, contextual information is used in less than half of the articles reviewed.

DISCUSSION

This review revealed that micro-level research on smallholders tends to be local in scope, data tends to be inaccessible for re-use, there is a narrow focus on specific analytical methodologies, and findings are difficult to generalize and re-use. These factors contribute to a rather fragmented body of knowledge. Admittedly, it is difficult to synthesize knowledge for policy use from the findings of many micro-level studies (Laborde et al., 2020). However, improvements could be made by improving data handling practices, broadening the suite of analytical approaches commonly used, and exploring more systematically the multi-level relationships between smallholders and their environmental and socio-economic context (van Wijk, 2014). We discuss below how the evidence from this review, the evidence from the literature, and the broader best practice guidelines can help inform the design of a more coherent research landscape, which facilitates continuous knowledge synthesis and systematic investigation of smallholder contexts. We explore the potential of meta-analysis (Gurevitch et al., 2018); and also discuss levers of behavioral change in this field of research. Finally, we discuss the limitations of this systematic review and how it limits the claims which we can make on these topics.

TABLE 7 | A cross tabulation of the coverage of the data used in the article, compared to the scale of recommendations made in the articles reviewed.

		Scale at which recommendations made						
		Local	**Sub-national**	**National**	**Regional**	**Global**	**All smallholders**	**Similar locations**
Data coverage	Local	10	5	4	2	1	13	1
	Sub-national	0	16	13	2	1	18	2
	National	0	0	8	0	0	3	0
	Regional	0	0	0	1	0	0	0
	Global	0	0	0	0	1	0	0

Numbers in the table represent percentages of all articles. Articles where it was not possible to determine data coverage or recommendation scale were not included in the cross tabulation.

TABLE 8 | Cross tabulations of articles' scale and the practices.

			Open data			Generalization of findings			Analysis methods		
		Percentage at spatial scale	**Data newly shared**	**Data public**	**Data not shared**	**Recommendation matches sample**	**Recommendation beyond sample scale**	**Contextual data used**	**Descriptive statistics**	**Single level linear or logistic regression**	**More complex methods**
Spatial scale	Local	31	2	1	28	5	22	11	28	20	13
	Sub-national	48	8	2	38	10	32	13	46	31	17
	National	11	2	5	5	7	3	5	11	8	6
	International	2	0	2	0	1	1	1	2	1	0

Each number represents the percentage of total articles. Only articles where it was possible to determine the spatial scale of the datasets are included.

Fair Data

This review has shown that, in many instances, data in micro-level research on smallholders was not findable, accessible, interoperable, or re-useable (FAIR) (Wilkinson et al., 2016). Data was often not shared, and where it was shared it was scattered across a range of repositories. Data that had been shared was rarely documented. Datasets often did not collect GPS information, and there was poor harmonization of measures collected for each study, limiting the ability to link newly collected data with other datasets. All these findings limit the ability to re-use data for meta-analysis and knowledge synthesis. Three particular issues hamper the creation of FAIR data in micro-level research on smallholders: (1) the lack of standardization in household surveys, (2) non-standardized meta-data, and (3) variation in approaches to sampling.

Survey Harmonization

The review has shown that household-level data often covered a similar range of topics (such as farm characteristics and access to resources), but variables or indicators were rarely harmonized between studies, making them incomparable. As 95% of the household-level datasets reviewed drew on structured surveys, we suggest that survey harmonization should be a top priority. Other domains facing similar challenges have pursued a modular approach to survey design. In a modular survey, a core set of questions is used to collect information common to many studies and optional modules are added to the survey to answer specific questions. This approach has been used by the UK's Office of National Statistics (ONS) to standardize household surveys, and the World Health Organization (WHO) to standardize health interview surveys (de Bruin et al., 1996; Smith, 2009).

For agricultural research, survey modules could be designed by the agricultural research community using community standards and ontologies. The CGIAR's working group on ontologies provide ontologies on a range of topics, including socioeconomics and agronomy (Arnaud et al., 2020). Digital data-collection tools, which can draw on a bank of standardized modules have an important role to play. There are several initiatives working toward standardized surveys on smallholders. The World Bank's LSMS-ISA (Osabohien, 2018), the Rural Household Multi-Indicator Survey (Hammond et al., 2017) and the CGIAR's 100Q initiative (van Wijk et al., 2019). The LSMS-ISA is a detailed survey, consisting of multiple rounds of data collection. The Rural Household Multi-Indicator Survey (RHoMIS) is a rapid survey, covering a range of topics using a lean-data approach. The 100Q initiative is a set of 100 questions, designed to accompany any smallholder household-level survey. This review has demonstrated that small-scale studies, with smaller sample sizes, make up the bulk of academic research on smallholders. As such, more agile tools which are less resource-intensive, like RHoMIS and the 100Q initiative, may be more equipped to deal with the challenges of small-scale research.

Metadata and Study Context

To enable meta-analysis and multi-level analysis, data standardization also needs to take place above the household level. A clear example of the importance of study context for meta-analysis is provided by Sibhatu and Qaim (2018). This meta-analysis examined the relationships between production diversity, diets, and nutrition for smallholders. It identified positive associations between production diversity and dietary diversity in some locations, and negative associations in others. The study used location and sample characteristics as variables in their meta-regression and found that these data were able to account for some of the differences between study findings.

This review showed that few studies provided meta-data in a standardized way. Meta-data generally came in the form of a site description, which included information on local climate, common crops grown, and common farming systems. The variables provided in site descriptions were rarely harmonized, and information was provided in various locations throughout the manuscript. It was observed that sampling procedures and statistical representativeness were not clearly documented in many of the studies reviewed. The common practices identified in this review, regarding meta-data and sampling, would not enable such meta-analysis to be conducted for most of the micro-level research on smallholders.

We recommend that researchers draw upon guidelines from other fields. The STROBE statement is particularly relevant for the reporting of observational studies (Field et al., 2014). This statement outlines what information on "setting" should be reported, including requirements for contextual information and sampling procedures. However, this checklist is generic, and the agricultural research community must still develop an approach which properly defines the context of a smallholder farm.

Transferrable Findings

This review also identified several key issues relating to the analysis methodologies used in micro-level research on smallholders. Unclear and unpublished analysis methods made it difficult to replicate findings, or to apply the same methodology to a new location. Regression findings were generally presented in a tabular format with an R-squared and a p-value for each covariate. While useful for interpretability, this approach makes it difficult to test the power of a model in another location. This is particularly problematic considering that many articles were local in scale.

There are multiple ways researchers could improve the transferability of findings. By focusing on reproducibility, researchers can allow their methods to be tested in new locations. To begin with, researchers need to specify the software they are using to analyze their data. Where possible, scripted languages, such as R, Python, or Stata should be used to conduct analyses, and these scripts should be shared and usable. If using a graphical user interface (GUI) software, such as Excel, tools are available to facilitate reproducibility (The Turing Way Community et al., 2019). Publishing regression findings in a standardized way, and sharing these findings in a data repository, could facilitate meta-analysis. In the health sciences, there is a catalog of guidelines on reporting findings (Simera et al., 2010). For example, reporting only p-values limits how findings can be subsequently incorporated into a meta-analysis, where at least confidence intervals should be reported for analytical power. The STROBE guidelines provide information on how to present statistical findings using a range of methods (Field et al., 2014). The TRIPOD guidelines outline procedures to present prediction findings, including guidance on variable selection methods (Collins et al., 2015). Finally, publishing data sources used in the analysis would allow users to replicate previous findings, and test models on new datasets.

The review identified a clear preference for descriptive statistics and linear or logistic regression. A narrow focus on any particular analysis methods can limit study design and has an effect on the type of research questions which are asked (Carletto et al., 2015). A more diverse research landscape, with balanced use of methods can facilitate innovation (Petrescu and Krishen, 2019). For example, multi-level correlations between covariates should be modeled using random effects through multi-level modeling techniques, while repeated measurements could be handled through random effects, curve fitting or time series modeling as appropriate. The CERES2030 reviews demonstrate that rural development research must consider a diverse range of outcome variables, and the complex interactions between household level determinants (Laborde et al., 2020). The use of models which can balance multiple objectives is essential. Few of the studies examined in this review compared the utility of different modeling approaches. The STROBE checklist also requires information on model selection criteria.

Reorientation of Manuscript Culture

Encouraging researchers to adhere to best practices will require some reorientation of research culture. Researchers are career driven, and often have high demands on their time. Research output is often measured using publication metrics, although this is changing. The data collected for a study and the methods used in analysis are also valuable contributions to science. *Data in Brief*, and *Scientific Data* are journals which provide mechanisms for research data to be cited when it is used. *MethodsX* is a journal which provides the opportunity for analysis methods to be cited also. Individual researchers aiming to capitalize on these initiatives should harness harmonization and standardization tools to ensure their data and methods are easy to re-use.

There are key levers of change which can be used to encourage adherence to best practices. Funding bodies, journals, and research organizations all have the power to influence research practices and encourage or enforce open research principles. The majority of peer-reviewed publications examined in this study did not share data or methods, indicating significant room for improvement. Reviewers should also consider how they evaluate a study's impact. A significant proportion of the articles reviewed in this study made claims beyond the scope of their data. Researchers are often required to argue for the impact or wide-ranging interest of their work, which is often linked to the spatial scale of their findings. We suggest that reviewers should consider whether claims of impact are supported by the data. Knowing exactly where findings apply, where they do not, and how research findings can be transferred to other contexts should be a key point of evaluation for reviewers.

Limitations and Future Research

This review highlighted key challenges in micro-level research on smallholder farmers. However, systematic reviews are inherently narrow in scope, focusing on specific research questions. This review examined only the most recent research to understand adherence to recent best practice guidelines. As such, research conducted prior to January 2018 has not been examined. Given that data-sharing and best-practices have grown in recent times, it is likely that the problems identified in this review are more prevalent in articles published prior to those reviewed.

This review also only examined academic research. This likely explains why common public datasets (such as the World Bank's LSMS-ISA) appeared relatively infrequently. Despite this, arguments for adherence to best practices still stand. While the World Bank and other sources of gray literature have shared their data, a significant proportion of rural development research takes place in smaller organizations which do not have the same requirements for data sharing and standardization. It is likely that the problems identified in this review also go far beyond academic research. Finally, this review aimed to examine broad issues in research, covering data acquisition, analysis methodologies, and interpretation of findings. Each of the issues covered in this broad review could benefit from further examination. In particular, investigation of the exact variables collected, and how variables differed between studies, would support the development of more useful ontologies. Further examination of how regression was used, how models were selected, and how findings were presented could support the design of specific reporting guidelines for micro-level smallholder research. Finally, a more specific focus on sample descriptions could help develop procedures and ontologies that describe sample context.

CONCLUSION

This review pointed to several issues which limit the potential for micro-level research on smallholders to generate coherent and widely applicable findings. The lack of harmonized metadata makes it difficult to compare the findings of two or more studies, for example through meta-analysis. The lack of harmonized microdata makes it difficult to conduct multi-level studies, comparing the impact of household level determinants and contextual determinants on key outcome metrics such as poverty and food security.

We propose that solutions to this entail following best practices in regards to: (a) data sharing, harmonization, and interoperability; (b) generation of more transferable findings by systematic description of study contexts and a more considered application of analysis methodologies; (c) a re-orientation in the culture of manuscript writing, whereby claiming unjustifiably wide spatial relevance is not valued, but instead contributing to knowledge synthesis is more highly valued. Particularly relevant are the FAIR principles. Central to the FAIR principles is the concept of actionability. Researchers must consider how their assets and findings are presented, prioritizing actionability. Parallel efforts in other research domains such as the health sciences could be of use. Building on such initiatives, like the STROBE and TRIPOD statements, the agricultural research community need to consider how their work can be presented in a way which can contribute to knowledge synthesis efforts. These steps would help leverage greater impact from the substantial investments already made in household level data-collection on smallholder farmers.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

LG conducted the review and analyzed the results. LG designed the study with support from JH. LG wrote the manuscript with support from JH, AWD, and WJB. All authors discussed the results and contributed to the final manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2021.727425/full#supplementary-material

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Smallholder Farmer Engagement in Citizen Science for Varietal Diversification Enhances Adaptive Capacity and Productivity in Bihar, India

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There is evidence that in many situations the use of a diverse set of two or more crop varieties in the field has benefits for production. The benefits of varietal diversification include lower crop disease incidence, higher productivity, and lower yield variability. Targeted interventions could increase varietal diversity where smallholder farmers lack the knowledge and access to seeds needed to diversify their varieties. Innovations based on crowdsourced citizen science make it possible to involve a large number of households in farmer participatory varietal selection. This study analyses varietal diversification in Bihar, India, focusing on the effects of the largest citizen science-based intervention to date, involving 25,000 farmers and 47,000 plots * seasons. The study examines if an increase in the varietal diversity of major staple crops, namely wheat and rice, under real farming conditions contributed to: (1) crop productivity and (2) the ability of households to recover from agricultural production shocks. We used the Rural Household Multi-Indicator Survey (RHoMIS) as a survey tool for rapid characterization of households and the sustainable rural livelihoods framework to understand the potential multiple interactions that are activated within the system by the intervention. We found that an increase in varietal diversification produced livelihood benefits in terms of crop productivity and the ability of households to recover from the occurrence agricultural shocks. Finally, outcomes highlight the effectiveness of development programmes aimed at strengthening rural livelihoods through participatory approaches and use of local crop varietal diversity.

Keywords: varietal diversification, citizen science, livelihood benefits, sustainable rural livelihoods, India, RHoMIS

INTRODUCTION

Smallholder farmers are exposed to growing uncertainty and risks (IPCC, 2014; Castells-Quintana et al., 2018). Weather disturbances are increasingly affecting agricultural systems and alternative sources of income are often limited (Lobell et al., 2011; Gitz and Meybeck, 2012). The likelihood for an agricultural system to be adversely affected by climatic stressors depends on both social and biophysical factors (Nelson et al., 2009). Vulnerability is a result of exposure and sensitivity of agricultural systems to climatic variation, as well as the capacity of producers to adapt within their livelihood systems (Turner et al., 2003; Adger, 2006). Short-term and long-term climate variation can jointly contribute to vulnerability. For example, smallholders might erode their assets and resources to cope with the short-term consequences of climatic shocks, and thereby undermine their long-term adaptive capacity (Otto et al., 2017; Call et al., 2019; Hansen et al., 2019).

Smallholders can adopt different strategies in response to climate stressors. These strategies include a more efficient use of the production factors (including natural resources) (Paavola, 2008; Speranza, 2013), changes in production technology through the introduction of novel crop management techniques or the adoption of stress-tolerant varieties or crops (Cho et al., 2014; Moniruzzaman, 2015; Mutabazi et al., 2015; Salazar-Espinoza et al., 2015; Call et al., 2019). Different strategies can help households to manage risk through resource allocation (Ellis, 2000) or (financial or non-financial) insurance (Yachi and Loreau, 1999; Barrett et al., 2001). Unfortunately, smallholders often lack the capital or knowledge to effectively implement some of these strategies (Gallopín, 2006; Burnham et al., 2018). Thus, farmers tend to manage risk largely through seed management, as well as through labor and land allocation (Di Falco et al., 2007).

An important option for responding to climate risk is on-farm diversification. It may be achieved through the diversification of the portfolio of farming-generating activities through increasing the types or varieties of crops in the field (Di Falco et al., 2011), crop rotation (Helmers et al., 2001), intercropping (Raseduzzaman and Jensen, 2017), integration of crops and livestock (Yesuf et al., 2008; Di Falco et al., 2011) or integration of trees into crop and/or livestock systems (i.e., agroforestry) (Verchot et al., 2007; Hansen et al., 2019).

In this paper, we focus on the use of a diverse set of two or more crop varieties on farms. This strategy relies on the genetic diversity among the range of varieties used by the farmer. Varietal diversity can help the farming system to buffer against adverse environmental conditions (Wolfe, 1985; Lannou and Mundt, 1996; Akem et al., 2000; Zhu et al., 2000; Østergård and Jensen, 2005; Kiær et al., 2009). There is evidence that varietal diversification can reduce crop disease through three mechanisms: (a) reducing the spread of pathogens, (b) increasing the distance between sensitive host plants, or (c) increasing the presence of resistant plants that form a barrier to prevent dispersion of pathogens (Chin and Wolfe, 1984; Smithson and Lenne, 1996; Finckh and Wolfe, 1998; Mundt et al., 1999; Zhu et al., 2000; Mundt, 2002). Further studies provided empirical evidence that variety richness is associated with an increase of productivity and a reduction of yield variability (Yachi and Loreau, 1999; Østergård and Jensen, 2005; Di Falco et al., 2007). Varietal diversity reduces yield variability because different varieties respond in different ways to different stresses. Different varieties can be combined into a portfolio that has a more stable average yield than any of the individual varieties (Nalley and Barkley, 2010; Sukcharoen and Leatham, 2016). The risk-buffering effect of variety portfolios is one reason why rural households often maintain more than one variety on their farm (Jarvis et al., 2008; Bellon et al., 2015a).

The above-mentioned studies analyzed the benefits generated by a varietal diversification strategy mainly through two types of studies. Observational studies look at empirical relationships in existing farming systems (e.g., Di Falco et al., 2007). Experimental studies look at biological mechanisms and experimentally control for a large number of factors (e.g., Nalley and Barkley, 2010; Sukcharoen and Leatham, 2016). Even though there is evidence for a causal relationship between varietal diversity and positive livelihood outcomes, neither type of study provides evidence that interventions that introduce new varieties succeed in activating this causal mechanism. Several things could stand in the way. Smallholder farmers may lack the knowledge needed to properly manage and deploy the varietal diversity available to them (Mulumba et al., 2012; Nankya et al., 2017). Farmers themselves can generate new knowledge to enable varietal diversification, but this requires them to be able to identify those varieties that are suitable for risk reduction and yield increase under diverse field conditions (Creissen et al., 2016; van Etten et al., 2019). To test if varietal diversification leads to positive livelihood outcomes under real conditions, a third type of study would be needed, focusing on the effectiveness of concrete interventions in shaping the nexus between the smallholder's adoption of the varietal diversification strategy and the livelihood benefits at household level.

Until recently, such interventions were rarely conducted at scale. Under real farming conditions, for a farmer, the variety selection process can be time-consuming and costly (Joshi et al., 1997). Also, farmer demand for a diverse set of varieties needs to lead to a more regular supply of these varieties by modern plant breeding and the commercial seed sector, which often struggles to create and distribute varieties suited for marginal niches (Ceccarelli, 1989; van Etten et al., 2017). Even though participatory varietal selection is now a legitimate exercise in crop research, the demand expressed by farmers is not always translated into breeding and seed production decisions (Sumberg et al., 2013). This requires that expressed demand for varietal diversity has a certain critical mass and is expressed in terms of the key decisions to be taken. Recent innovations make participatory varietal evaluation more scalable, more diversity-oriented (more varieties in the trials) and more informative regarding environmental adaptation. van Etten et al. (2019) have shown that crowdsourced citizen science can support farmer evaluation of varieties to include a much larger number of farmers and varieties in participatory trials than was previously possible. They also showed that varietal evaluation based on citizen science can generate results that show quantitatively the causal effect of seasonal climate on crop variety performance.

The present study examines the effect of smallholder adoption of varietal diversification as a livelihood strategy and the livelihood benefits at household level that ensue, evaluating an intervention using the citizen science approach to varietal evaluation introduced by van Etten et al. (2016, 2019). This intervention took place in Bihar, India from 2010 to 2017 and focused on rice and wheat.

We assume that this development programme represents an exogenous change of the institutional context that provides a quasi-experimental framework that allows to better identify the outcomes of varietal diversification as an intervention strategy. We focus on two specific potential benefits of varietal diversity: (1) crop productivity, and (2) the ability of households to recover from agricultural shocks. We compare the responses between households who obtained seeds and knowledge on how to diversify the variety portfolio and households who were not directly exposed to the development intervention and have managed their farming practices as usual.

The current analysis is structured as follows: section Conceptual Framework presents the theoretical approach adopted; section Study Context introduces the S4N initiative and the context in which it was carried out; section Methodological Approach describes the data collection process, the outcome variables of interest and the methodological approach to the analysis; while sections Results and Discussion report and discuss the main results and their implications. The study ends with some concluding remarks.

CONCEPTUAL FRAMEWORK

The current study aims to investigate if the implementation of a varietal diversification programme is associated with: (1) a change in the farming strategies implemented by the rural households and (2) derived livelihood benefits at household level. In order to assess this objective, the theoretical foundation of this study relies on the Sustainable Rural Livelihoods (SRL) framework (**Figure 1**) (Scoones, 1998; Bebbington, 1999; Carney, 1999; Ellis, 1999; Niehof, 2004; Martin and Lorenzen, 2016). The advantage of the SRL approach is that it provides a framework for a holistic interpretation of the dynamics of development (Helmore and Singh, 2001; Butler and Mazur, 2007). Indeed, it proposes a comprehensive insight that emphasizes the livelihood system of rural households and analyses the ways in which they adapt their farming strategies to manage external changes to preserve their livelihoods (Scoones, 1998).

In the SRL framework, changes in the institutional context can affect livelihood outcomes in two ways. One is an indirect route through changes in livelihood assets and the capacity of these assets to cope with the vulnerability context, which can enhance or diminish the overall livelihood strategy and thereby affect livelihood outcomes. A second route is that institutional change can affect livelihood strategies directly and thereby affect livelihood outcomes.

Our study focuses on this second route: how can a change in the institutional context, the participation of farming households in a more information-rich environment about the performance of assets (crop varieties), affect their livelihood strategy and holding a broader portfolio of livelihood assets (varietal diversification)? Within the SRL framework, this paper mainly focuses on the role of the institutional context, aiming to identify its effective impact on shaping the relation between the smallholder's adoption of a specific livelihood strategy and the resulting livelihood outcomes. Modest but well-targeted changes in the institutional context can make adaptive strategies more efficient and even sustainable in the long term, thanks to the potential multiple interactions that are activated within the system (Helmore and Singh, 2001; Butler and Mazur, 2007). Such changes can consist in targeted scientific advice, improved technologies, financial facilities, or changes in government policies.

More in detail, following the SRL framework, the livelihood system of the rural households is based on three main elements: livelihood assets, livelihood strategies and sustainable livelihood outcomes. The asset base upon which households build their livelihoods comprehends a portfolio of five different types of assets: natural, financial, physical, human and social capitals (Scoones, 1998). A household will combine the different categories of assets available to it in a strategy designed to accomplish desirable livelihood outcomes (FAO, 2019). However, a household will modify its farming practices to cope with the various challenges coming from the outside system. The outside system is composed of the vulnerability context and the institutional context, which are both the entry points for development initiatives. The vulnerability context refers to the unpredictable events that are beyond the control of the household and can undermine their livelihoods. The institutional context refers to a set of formal and informal institutions and organizations that mediate the ability to implement specific strategies and achieve tangible results. This aspect is of particular interest in the SRL framework. Indeed, policies, institutions and processes influence how households use their assets to pursue different livelihood strategies. Household assets interact with structures (government and private sector) and processes (policies, laws and institutions) responsible for social, economic and political transformation that can shape the vulnerability context, the access to the assets and the choice of livelihood strategies (Adato and Meinzen-Dick, 2002). This may take place on multiple levels, from the household to community, national and even global levels. The institutional focus of the SRL approach gives a practical gain when considering policy applications, by identifying the structures that play an important role in resource allocation, and by identifying social rules and norms that would have an impact on the outcome of an external intervention (Brock, 1999). This makes it possible to observe how policies and programmes are able to influence the households' portfolio of assets and the vulnerability context of reference and how this, in turn, leads to the adoption of specific strategies capable of managing the negative impacts on income and food security caused by extreme climatic events, uncertain agricultural production and unexpected market shocks.

The analysis perspective offered by the SRL framework makes it an adequate theoretical framework for the current analysis, as it highlights the potential multiple interactions that are activated within the system following a change in the institutional context. The next paragraph will provide a more detailed picture of the study context.

STUDY CONTEXT

This study focuses on the Seeds for Needs (S4N) initiative. S4N started in the 2010 and has been implemented in 14 countries in Africa, Asia and Central America with the aim of

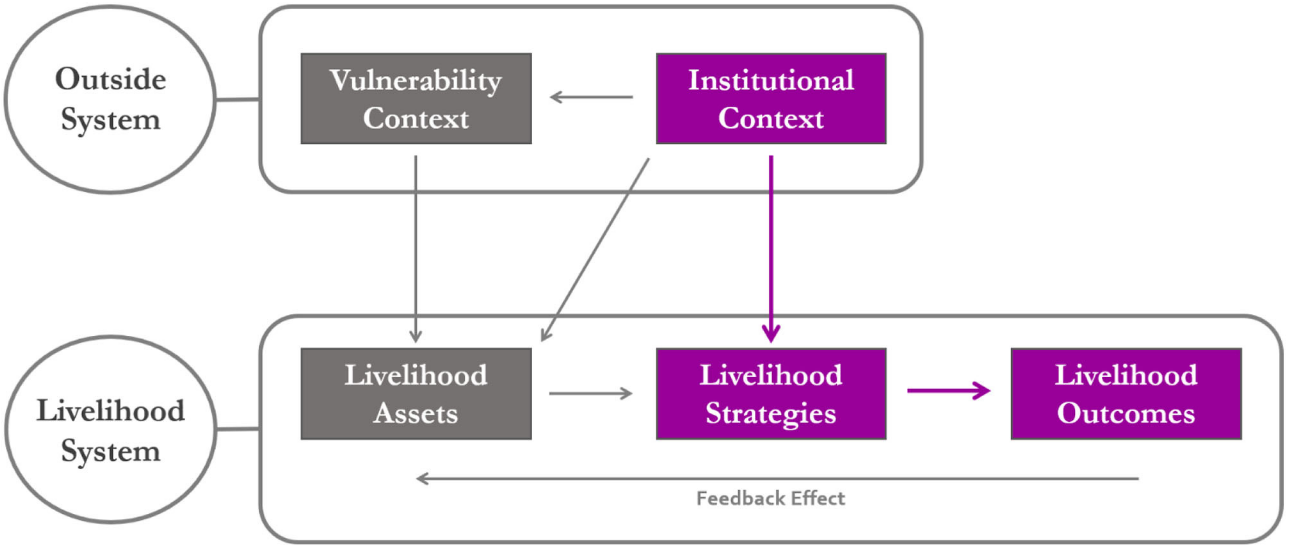

FIGURE 1 | The sustainable rural livelihood framework. Source: adapted from Scoones (1998) and Carney et al. (1999).

promoting and using the diversity of plant genetic resources as a means to reduce farmers' vulnerability to climate change (van Etten et al., 2016; Bioversity International, 2018). More specifically, the main component of the S4N initiative addressed the scarce availability of stress-tolerant cultivars, as cropping systems' adaptation requires the continuous delivery of varieties able to address "genotype by environment" interaction (van Etten et al., 2019). After seed varieties that are potentially adapted to the local agroecological and climatic conditions were identified, they were distributed to farmers for participatory selection by means of on-farm experiments in collaboration with scientific and extension staff (Dawson et al., 2008). The range of collaborative research activities engaging farmers together with scientist is defined as "citizen science," an emerging trend that enables research and development (R&D) to be faster, larger in scale and more focussed on addressing community needs and contextual factors (Resnik et al., 2015), in this case, in terms of agricultural research (Ryan et al., 2018). A second, complementary component addressed the need to raise farmers' awareness by conducting capacity-building activities on sustainable production techniques and the importance of a diversified agricultural production. Trainings were conducted in the form of Farmer Field Schools (FFS), a bottom-up and participatory approach used by scientists and national extension officers to engage with smallholder farmers (Braun et al., 2000). These trainings were based on a "learning by doing" concept and were meant to build farmers' capacity for informed decision-making through hands-on experimentation and frequent interaction for knowledge and experience sharing (Chandra et al., 2017). For the above-mentioned characteristics, Nelson (2020) recognized the S4N initiative as effective implementation of the participatory approach.

In India, the S4N initiative has involved over 25,000 farmers from 600 villages of 49 districts in 7 states, participating as "citizen scientists" in around 46,000 participatory varietal trials (Bioversity International, 2017; van Etten et al., 2019). In this study, we analyse the resulting outcomes of the activities carried out in India, in the Vaishali district of Bihar[1] that started in 2010. For the current analysis, the State of Bihar was chosen as a case study for two reasons: firstly, it is the State where S4N implementation first started, offering the possibility to study the potential benefit of a change of the institutional context affecting the livelihood strategies over a longer time span. Secondly, Bihar is one of the most climate-sensitive states in India. Rainfall fluctuates greatly from one season to another; it is also densely populated, with high levels of poverty and 90% of its rural dwellers are directly employed in agriculture (Tesfaye et al., 2017; Pagnani et al., 2021) with land holding sizes of <2.5 acres.[2]

The implementation of this initiative in Bihar provides a source of exogenous change to the institutional context, which allows the social scientist a better perspective for an empirical identification of the link between the different domains of the SRL framework. Indeed, thanks to the institutional activities, it is possible to compare the livelihood strategies and their outcomes for households under the effect of an institutional change with a counterfactual provided by similar communities and households that were not explicitly covered by the S4N development initiative.

[1]Since 2011, the S4N initiative has been further extended to nine more Indian states: Uttar Pradesh, Odisha, Madhya Pradesh, Chhattisgarh, Orissa, Punjab, Haryana, Jammu and Kashmir.

[2]Bihar ranks lowest amongst the other Indian states in terms of literacy and lags in socio-economic conditions compared with the national average. Due to high poverty, inequality and a poor education system, resulting from low investment and poor governance, Bihar has poor education and health conditions. The population density in Bihar is double (800 persons/km²) the national average (329 persons/km²) (Rasul and Sharma, 2014).

The hypothesis is that the S4N approach can improve the livelihood strategies of smallholder farmers and influence their livelihood assets. Particularly, the intervention provided knowledge, skills and practices to enhance the human capital of those who actively participated in the process. At the same time, the distribution of new, potentially-suitable seed varieties contributed to the improvement of their natural and physical capital. Finally, the participatory approaches of S4N encouraged the connection between farmers within and across communities, expanding the social capital of the rural households.

The changes affecting the human, natural and social capital of smallholder farmers will in turn lead to the adoption of the crop varieties promoted by the initiative, thus increasing the genetic diversity in their fields. Finally, farmers who adopt varietal diversification strategies can obtain further livelihood benefits in terms of: (1) crop productivity, and (2) the ability to recover from the occurrence of agricultural shocks.

METHODOLOGICAL APPROACH

Data

The data used for this analysis are generated from a household questionnaire administered between February and August 2018 (Gotor et al., 2018). Data are available for 600 stratified, randomly selected rural households of three districts of Bihar: Saran, Samastipur, and Vaishali. The three districts have been identified as particularly vulnerable through regional workshops and therefore suitable for the implementation of climate-smart agriculture under the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

The S4N initiative was executed with financial support from the Indian government and strong partnership with national institutions. Expansion of the field activities during the project responded dynamically to local demand and capacity. This precluded the ex-ante definition of project outcomes and thus the execution of a sounding baseline data collection or randomized selection of households or communities. The fact that the S4N initiative did not have *a priori* control group restrict the options to create a proper counterfactual (Gotor et al., 2017). Furthermore, participation in the initiative was open to all community members and was voluntary. To address these issues, a stratified random sample was drawn based first on the selection of the villages where the initiative was carried out and then on participation in the initiative. Finally, the households within the villages were randomly selected from household lists obtained by local authorities. In total, 12 villages from three districts of Bihar (Saran, Samastipur, and Vaishali[3]) were identified and 600 rural households were selected, of which 300 participants and 300 non-participants.[4] More in detail, the treatment or *exposed* group consisted of 300 households drawn randomly from project records within the identified villages, while the control or *non-exposed* group consisted of 150 randomly selected non-participant households within the 12 villages as the exposed group and of 150 households from 9 other villages that were similar and proximate, but where the initiative had never been implemented[5] (**Table 1**). The random assignment of the subjects to the *non-exposed* group increases the validity of the assessment; however, since the group of participating households has not been randomly assigned to the *exposed* group, specific statistical adjustments need to be implemented in the empirical analysis, as described in the Empirical Analysis section.

TABLE 1 | Sample composition, number of households per group and villages.

District	Village	Exposed group	Non-exposed group	Total
Saran	Bhagwanpur	3	15	18
	Dharmagt Tola	0	19	19
	Khanpur	0	19	19
	Rampur Jaitti	18	21	39
	Sabalpur	8	13	21
	Sultanpur	10	24	34
Sub-total		39	111	150
Samastipur	Dhobgama	0	20	20
	Harpur	32	16	48
	Madapur	14	5	19
	Mahamada	36	12	48
	Narayanpur	0	17	17
Sub-total		82	70	152
Vaishali	Bhathadasi	57	28	85
	Fatehpur Chauthai	0	18	18
	Kariyo	10	3	13
	Kutubpur	0	23	23
	Mirpur Patadh	0	5	5
	Mukundpur	31	2	33
	Panapur	4	1	5
	Rajapakar	77	10	87
	Sembhopatti	0	20	20
	Vishanpura	0	9	9
Sub-total		179	119	298
Total		300	300	600

The data collection team was composed of three enumerators. One of them was appointed team leader and was in charge of cross-checking all data at the end of each day. Enumerators attended a series of four full-day training and field-testing sessions. Questionnaires were translated into Hindi, the local language, for better comprehension of enumerators and farmers. Electronic tablets were used to record the data using the Open Data Kit (ODK) platform (Hartung et al., 2010). At the end of each day, all household data was examined by the team leader and then uploaded to a server. The household questionnaire was composed of 17 sections, of which three were specifically

[3]Floods in Bihar during the southwest monsoons compromised the selection of some villages in the districts of Saran and Samastipur, making the sample skewed in favour of Vaishali district.

[4]From project records, a total of 6,500 rural households participated in the S4N initiative, of which 1,500 in Saran, 1,500 in Samastipur and 3,500 in Vaishali.

[5]This study does not analyse the differences between the two different types of *non-exposed* groups, while they are considered as a unique group in the empirical approach. Households without cultivated land were excluded from the *non-exposed* groups.

TABLE 2 | Definition and descriptive statistics of variables employed in the empirical analysis.

Variable Name	Description	Non-exposed		Exposed		*t*-test[a]
		Mean	Std. dev	Mean	Std. dev	
Human capital						
Age of household head	Years of age	46.40	12.96	48.38	11.96	−1.95*
Education of household head	Level of education	3.04	1.67	3.16	1.54	−0.97
Household size	Number of household members	7.35	3.00	7.78	3.14	−1.71*
Social capital						
Gender of household head	Dummy variable: 1 = female, 0 = otherwise	0.23	0.42	0.25	0.43	0.45[a]
Trust in people	Dummy variable: 1 = people can be trusted, 0 = otherwise	0.48	0.50	0.78	0.41	59.32[a]***
Trust and cooperation community	Level of trust and cooperation among community members	2.07	0.73	2.40	0.68	−5.79***
Natural capital						
Land cultivated	Number of acres cultivated by a household	1.71	1.84	1.29	1.25	3.25***
Physical capital						
Inputs	Total inputs used by a household	5.84	0.40	5.78	0.72	1.13
TLU	Tropical Livestock Unit	0.82	0.85	0.79	0.91	0.50
Financial capital						
Off-farm income	Dummy variable: 1 = household engaged in off-farm activities, 0 = otherwise	0.83	0.38	0.84	0.37	0.19[a]
Debt	Dummy variable: 1 = household find difficult to pay debts, 0 = otherwise	0.52	0.50	0.60	0.49	3.90[a]**
Formal credit	Dummy variable: 1 = household access to formal sources of credit, 0 = otherwise	0.01	0.11	0.09	0.29	19.01[a]***
Informal credit	Dummy variable: 1 = household access to informal sources of credit, 0 = otherwise	0.02	0.14	0.04	0.20	2.66[a]
Vulnerability context						
Weather-related shock	Household exposure to pest & disease and climatic stressors	0.05	0.89	−0.05	1.10	1.15
Financial shock	Household exposure to decrease sales prices and assets shocks	−0.08	0.94	0.08	1.05	−1.90*
Livelihood outputs and outcomes						
Adoption rice	Number of initiative's rice varieties adopted by the household	0.20	0.50	1.65	1.08	−21.08***
Adoption wheat	Number of initiative's wheat varieties adopted by the household	0.31	0.61	1.91	1.12	−21.79***
Rice SDI	Measure of rice diversification in the field	0.60	0.22	0.62	0.22	−1.32
Wheat SDI	Measure of wheat diversification in the field	0.56	0.21	0.60	0.22	−2.33**
Rice PYC	Perceived rice yield trend (5 years)	0.67	0.95	0.92	1.00	−3.14***
Wheat PYC	Perceived wheat yield trend (5 years)	1.10	0.96	1.37	0.91	−3.59***
Recovery capacity	Household's ability to recover from shocks	1.44	1.43	1.52	1.46	−0.62

*t-test H_0: diff = 0. Level of significance: *10%; **5%; ***1%.*
[a]*Pearson χ^2 test implemented in case of dummy variables. Vectors of means are equal for the two groups, $F_{(22, 577)} = 30.7077$, Prob > $F_{(22, 577)} = 0.0000$.*

devoted to measuring the possible effect of the S4N intervention and focusing on the: (1) participation of farmers in the S4N activities, (2) households' exposure to shocks and their recovery capacity, and (3) detailed information on the wheat and rice cultivation (S4N target crops). For item (3), specific information was gathered on the number of wheat and rice varieties that were sown in the previous 5 years, the seed source, the characteristics of most-preferred seeds, the quantity produced in the last and second to last growing season, quantities consumed and sold, as well as the average market price. Moreover, the questionnaire explored the frequency of climate-induced harvest losses of rice and wheat cultivation, and a self-reported scale was used to assess the perceived extent of recovery following their occurrence. The remaining sections are adapted from the Rural Household Multi-Indicator Survey (RHoMIS), a household survey tool designed to rapidly characterize a series of standardized indicators across the spectrum of agricultural production and market integration, nutrition, food security, poverty and greenhouse gas emissions, as well as standard socioeconomic information on household demographics, education, landholdings, sources of income, migration and gender-disaggregated decision-making power allocation (Hammond et al., 2017). The survey was designed to reduce the time burden for interviews, to refine the accuracy of responses, and to maximize consistency between different studies. The RHoMIS questions were tailored following enumerators' feedback during the training.[6].

Indicators

The Simpson's Diversity Index (SDI) (Simpson, 1949) is used to test the hypothesis that on-farm exposure to new varieties of wheat and rice led to a higher varietal diversity. This index is among the most suitable indexes for measuring crop

[6]The original data and the survey are available on request at the following doi: 10.7910/DVN/DW2W9J.

diversification patterns and is calculated as:

$$Simpson's\ Diversity\ Index\ (SDI) = 1 - \sum_{j=1}^{J} P_j^2$$

where $P_j = A_j / \sum A_j$ is the share of the j-th varieties area over the total cultivated area for the specific crop. Value ranges start at zero (0) (only one variety cultivated), and approach 1 when many varieties are cultivated in equal shares.

Following Gotor et al. (2013), the effect on crop productivity was measured in terms of perceived change of yield (*PYC*) over the last 5 years. This is a self-reported measure, which ranged from −4 (100% decrease of yield) to 4 (increase of 100% or more). The variable assumes a positive (negative) value equal to 3, 2 or 1 when the household perceived an overall yield increase (decrease) of respectively ∼75, 50, and 25%.

Moreover, the model controls for both financial and weather-related shocks. A specific set of questions was formulated to capture the ability of households to recover from them. To obtain a measure of ability to recover, households self-assessed their capacity to recover from: (a) a decrease in the sale price, (b) a shock affecting their assets, (c) an increase of pest and disease occurrence, and (d) from direct climatic stressors. Based on the answers to these recovery capacity questions, a cumulative variable on the household recovery capacity (*RC*) was constructed. We summed the frequency of positive (+1) and negative (−1) answers indicating their ability to recover from shocks. If the household declared that it was not exposed to the specific shock, it was counted as a 0 response. Thus, *RC* values can range between −4 and +4.

Finally, the specific variables selected to define the different livelihood assets are based on the theoretical and empirical literature. Human capital is associated with the age and level of education of the household head, as well as the number of household members. Social capital is associated with the gender of the household head and a self-assessment of trust in people and levels of trust and cooperation within the community. As concerns the former, female-headed households generally face greater social barriers that may limit their access to information and other resources (Tenge et al., 2004; García de Jalón et al., 2018). Natural and physical capital is associated with the extension of cultivated land and the total amount of agricultural inputs (i.e., fertilizer, manure, compost, pesticides, irrigation facilities, and tillage methods). Lastly, financial capital is represented by four different dummy variables based on: pursuit of off-farm income generating activities, ownership of debts, access to formal sources of credit (from the government, NGOs or other organizations) and access to informal sources of credit (from family, friends or neighbors). The description and descriptive statistics of the variables used in the empirical analysis are shown in **Table 2**.

Empirical Analysis

Two empirical analyses were carried out: the first analysis consists in the identification of the casual effect of the institutional context change on a set of key livelihood outcomes. The research hypothesis underpinning the overall study is that the household's exposure to the S4N intervention activities may provoke changes to the smallholder farmers' seed portfolio, increasing the genetic diversity in their fields, thus generating livelihood benefits for the households in terms of crop productivity and the ability to recover from agricultural shocks.

However, the institutional change does not occur randomly, since, even if there are households from communities that are not involved in the intervention, the sample obviously includes a group of households that have autonomously decided to participate in the initiative activities. Thus, the group of participating households has not been randomly assigned to the exposure, and therefore large differences in terms of compounding factors may exist between the two groups, yielding to biased estimates of the initiative's effects. For this reason, this empirical analysis relies on a specific estimator used in quasi-experimental study, the doubly robust (DR) (Bang and Robins, 2005), to quantify if any substantial differences between households participating in the initiative, compared to those that have not been involved, can be effectively attributed to the institutional change.

DR estimator combines two different approaches to estimate the causal effect of an exposure on the outcome: a specification for the outcome regression and a specification for the exposure. This ensures the robustness of the results because possible forms of misspecification of the model due to selection bias and confounding effects are both considered (Emsley et al., 2008; Caracciolo and Furno, 2017).

$$DR = \frac{1}{N}\sum_{i=1}^{N} \frac{\mathrm{W_i Y_i} - \left(\mathrm{W_i} - \widehat{p(\mathbf{x}_i)}\right)\hat{Y}_{i1}}{\widehat{p(\mathbf{x}_i)}} - \frac{1}{N}\sum_{i=1}^{N} \frac{(1-\mathrm{W_i})\,\mathrm{Y_i} + \left(\mathrm{W_i} - \widehat{p(\mathbf{x}_i)}\right)\hat{Y}_{i0}}{1-\widehat{p(\mathbf{x}_i)}} \qquad (1)$$

where $\mathrm{Y}_{i,1}$ is the observed outcome when the i-th household was exposed to the initiative and $\mathrm{Y}_{i,0}$ is the outcome if the household was not exposed, $\mathbf{x}_\mathrm{i}$ is a vector of the livelihood assets (capturing human, physical, natural, financial and social capital of the i-th household) and $p(\mathrm{X_i})$ the conditional probability of being exposed or propensity score ($\mathrm{W_i} = 1$) vs. unexposed ($\mathrm{W_i} = 0$):

$$p\,(\mathbf{x_i}) = pr\,[\mathrm{W_i} = 1|\mathbf{x}_\mathrm{i}] \qquad (2)$$

The second empirical analysis consists in the assessment of the specific consequentiality of the steps as theorized in the SRL framework, linking the livelihood benefits (i.e., positive change in productivity and capacity to recover) to the households' adoption of varietal diversification strategies and the institutional context. To assess the above-mentioned relationships, it is necessary to link how the exposure to the S4N activities may influence the on-farm varietal diversification, and if the latter can be reasonably linked to the yield change and the household recovery capacity to shocks. In order to test all the above-mentioned relationships, a simultaneous system of equation has to be formulated *ad hoc* and estimated via a Generalized Method of Moments (GMM).

The stochastic version of the system is formulated for the i-th household and for the j-th crop in the following way:

$$\text{Equations (1) and (2)} : SDI_{j,i} = x_i{}'\theta_j + \gamma_j Participation_i + \tau_j Adoption_{j,i} + v_{j,i} \quad (3)$$

$$\text{Equations (3) and (4)} : PYC_{j,i} = x_i{}'\alpha_j + \beta_j SDI_{j,i} + u_{j,i} \quad (4)$$

$$\text{Equation (5)} : RC_i = x_i{}'\omega + \sum_{j=1}^{J} \delta_j PYC_{j,i} + e_i \quad (5)$$

This system of equations explicitly analyses the dynamic linkages among initiative participation (*Participation*), adoption of the wheat and rice varieties supported by the initiative (*Adoption*) and initiative's outputs, such as varietal diversification measures (*Simpson's Diversity Index - SDI*). Moreover, it analyses the link between the initiative's outputs (*varietal diversification*) and two livelihood outcomes, the perceived change of yield (*PYC*) and the overall recovery capacity of the households from shocks (*RC*).

The system of equations includes as confounding variables the livelihood assets $\mathbf{x}_i$ (variables capturing human, physical, natural, financial and social capital of the i-th household) while θ, α, and ω are the parameter vectors of the equations' system that measure the effects of the livelihood assets on the dependent variables; while v_{ji}, u_{ji}, and e_i are the error components. Finally, the estimation of the parameters τ, β, and δ allows us to test the consequential links between the outputs and outcomes of the initiative. Indeed, through the estimation of the parameter τ, the model measures whether adoption of the varieties disseminated through the initiative affects varietal diversity of wheat and rice (Equations 1, 2). The β parameter tests, for each crop, the existence of a linear relation between the varietal diversity and the perceived change of yield (Equations 3, 4), while δ measures the association between the perceived changes of the two crops' yield and the i-th household's capacity to recover from shocks (*RC*) (Equation 5). Since two target crops exist, a total of five simultaneous equations will be estimated (two for the *SDI*, two describing the perceived change of yield and one for the overall recovery capacity).

The above-mentioned approach controls for reverse causality and other possible sources of endogeneity (Heckman and Vytlacil, 2005), conditionally on the variables chosen as instruments. Instruments have been selected according to the plausibility of the assumptions, as well as the outcomes of the diagnostic tests. Household participation to the initiative (yes or no) and the number of adopted wheat and rice varieties supported by the initiative have been used as instruments, assuming that they may influence the perceived change of yield only through the use of varietal diversification. Similarly, the varietal diversification is assumed to influence the households' recovery capacity only through an effect on the perceived change of yield. Finally, following Bellon et al. (2015b), households were weighted by the inverse probability (IPW) of initiative participation, which controls for potential sources of selection bias. The IPW weighting considers the observable differences of the livelihood assets between households that have the opportunity to be exposed to the initiative and the households that were excluded. Diagnostic tests were carried out to confirm the validity of the instruments (Durbin–Wu–Hausman test for endogeneity and the Weak Instrument test) (Cameron and Trivedi, 2005).

RESULTS

Sample Description

The mean value and the standard deviation of the variables employed in this study are shown in **Table 2**. The variables related to the five capitals (i.e., human, social, natural, physical and financial) are shown in top half of **Table 2**. The principal differences between the two groups (exposed and non-exposed)

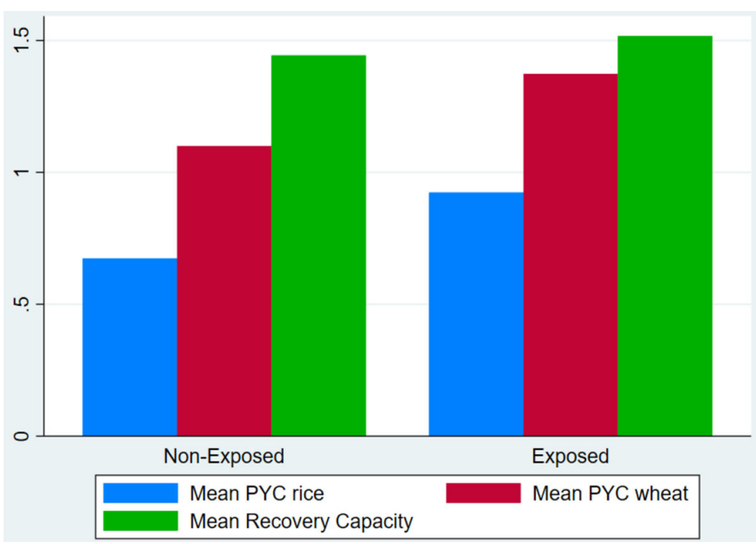

FIGURE 2 | Perceived change of yield (*PYC*) for wheat and rice, and recovery capacity index (*RC*) by exposure to the S4N initiative.

TABLE 3 | Results of the doubly robust estimator.

	Non-exposed	Exposed	DR estimate	*p*-value	Range	Benchmark[a]	DR estimate (%)[b]
Rice SDI	0.602	0.633	0.031	0.042	0–1	0.602	5.15
Wheat SDI	0.561	0.622	0.061	0.000	0–1	0.561	10.87
Rice PYC	0.690	0.875	0.185	0.053	−4; +4	4.690	3.94
Wheat PYC	1.102	1.347	0.245	0.016	−4; +4	5.102	4.80
Recovery capacity	1.377	1.778	0.401	0.001	−4; +4	5.377	7.46

[a] *Benchmark was rescaled adding 4 to the non-exposed value.*
[b] *Calculated as (DR estimate/Benchmark) × 100.*

are most notable in terms of human, social, natural and financial capitals. Households exposed to the initiative have on average a greater number of members and are headed by older people, besides having a higher level of confidence in people and among community members. Moreover, exposed households have a smaller extension of cultivated land (1.29 acres compared to 1.71 acres for the non-exposed), but exhibit a higher level of indebtedness (an average value of 0.60 compared to 0.52 for the non-exposed). The average size of the land holdings in Bihar is <2.5 acres (91% farmers), with that of marginal and small farmers ranging from 0.80 to 1.25 acres, respectively (Government of Bihar, 2020). They are often resource-poor farmers with lower ability to afford mechanization and services, due to which they exhibit a higher level of indebtedness. Compared to other north-western states of India, Bihar is characterized by poverty and high population density. Therefore, the farmers there are more prone to agricultural risks, which in turn leads to indebtedness. Conversely, we saw no significant differences in terms of physical capital between those exposed to the initiative and those who were not exposed.

When considering the variables related to the vulnerability context, the households participating in the initiative on average registered a higher exposure to financial shocks but a lower exposure to pest and disease, and climatic stressors. However, the difference among the two groups is statistically significant only in terms of exposure to financial shocks.

As expected, the number of varieties adopted by the households is higher for those exposed to the initiative, even if the differences in terms of varietal diversification between the two groups are not particularly evident (the differences between exposed and non-exposed are significant only for the level of varietal diversity of wheat). With regard to the perceived change of yield, the mean value of the exposed households is higher than the value of the non-exposed one (as can be seen from **Figure 2**). Lastly, data reported in **Table 2** show that there are no noticeable differences between exposed and non-exposed households in terms of the ability to recover from agricultural shocks.

S4N Initiative's Impact

As discussed in the previous paragraph, both exposed and non-exposed groups of households showed some differences in terms of livelihood assets. The DR estimator addresses this difference to allow for a proper comparison between the two groups. Results of the exposure equation are detailed in the Appendix (**Table A1**). Results of the DR estimator are shown in **Table 3**, identifying the effect of the institutional context change on livelihood outcomes. It is evident that exposure to initiative activities generated positive and significative changes on the variety portfolio of smallholder farmers, specifically on the varietal diversification of target crops. The Simpson's Diversity Index for rice was around 0.6 for the non-exposed and 5% higher (+0.03) for exposed households. The varietal diversity of wheat increased even more. In this case, Simpson's Diversity Index for wheat for non-exposed households was similar of those for rice (0.56), while the effect of participation in the initiative increased this to 11% (+0.06) (**Table 3**).

The DR results also confirm the research hypothesis underpinning the overall study, namely that exposed households can obtain livelihood benefits in terms of crop productivity and ability to recover from shocks. As can be seen from the equations we applied, the effect on the perceived change of yield is positive and significant. In this case, the impact generated by the S4N initiative was still higher for wheat: exposed households benefitted from an increase of the mean *PYC* value of 0.185 points for rice and 0.245 points for wheat, which corresponds to a yield increase of +3.94% for rice and +4.80% for wheat. Lastly, at the bottom of **Table 3**, the effect on households' recovery capacity is reported, showing an increase in their ability to recover from shocks of around 0.40 points in the *RC* scale ranging from −4 to +4 compared to non-exposed households that have an increase corresponding to around 7% of the actual mean value. The above-mentioned results could be considered a conservative estimate of the S4N initiative since they ignored the existence in the control group of any spillover effect.

Econometric Results

The last part of our analysis is based on the estimation of five simultaneous equations (**Table 4**). This analysis aims to test the Theory of Change based on the SRL framework. Equations (1) and (2) analyse the relationship between the change in the institutional context (measured in terms of participation in the activities proposed by the initiative and the intensity of adoption of the varieties promoted by the initiative) and the level of varietal diversity maintained on-farm by the households (proxied by the Simpson's Diversity Index).

The results of Equations (1) and (2) show a positive and significant relation between the adoption of the introduced varieties and the level of diversification, both for rice and

TABLE 4 | Results of the system of simultaneous equations.

	Equation (1) Rice SDI		Equation (2) Wheat SDI		Equation (3) Rice PYC		Equation (4) Wheat PYC		Equation (5) Recovery capacity	
	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value
Livelihood outputs and outcomes										
Participation	−0.029	0.231	0.019	0.265						
Adoption rice	**0.047**	**0.001**								
Adoption wheat			**0.028**	**0.000**						
Rice SDI					**1.968**	**0.009**				
Wheat SDI							**3.006**	**0.010**		
Rice PYC									0.260	0.746
Wheat PYC									**1.810**	**0.049**
Human capital										
Age of household head	0.000	0.694	0.000	0.541	0.000	0.964	0.001	0.819	−0.009	0.316
Education of household head	0.004	0.520	0.009	0.146	**0.093**	**0.014**	0.077	0.130	−0.186	0.088
Household size	0.002	0.450	−0.001	0.655	0.011	0.444	0.008	0.626	0.011	0.768
Social capital										
Gender of household head	**−0.060**	**0.018**	−0.040	0.105	**−0.262**	**0.052**	−0.266	0.104	**1.004**	**0.005**
Trust in people	0.028	0.291	−0.007	0.809	0.218	0.165	0.218	0.229	**−1.341**	**0.001**
Trust and cooperation community	**−0.053**	**0.001**	**−0.046**	**0.003**	−0.013	0.897	0.147	0.173	−0.241	0.279
Natural capital										
Land cultivated	**0.003**	**0.004**	**0.003**	**0.005**	**−0.011**	**0.072**	−0.004	0.566	−0.005	0.767
Physical capital										
Inputs	0.010	0.497	**0.046**	**0.007**	0.046	0.616	−0.145	0.141	−0.163	0.383
TLU	**0.031**	**0.002**	**0.019**	**0.042**	0.014	0.804	**−0.109**	**0.080**	0.018	0.917
Financial capital										
Off-farm income	−0.033	0.169	−0.001	0.958	0.105	0.461	0.032	0.854	−0.232	0.491
Debt	**0.067**	**0.000**	**0.047**	**0.007**	−0.011	0.911	−0.123	0.320	0.100	0.627
Formal credit	0.004	0.929	−0.035	0.625	−0.107	0.669	−0.062	0.862	0.366	0.530
Informal credit	**0.153**	**0.000**	**0.132**	**0.000**	**−0.438**	**0.091**	−0.389	0.287	0.175	0.782
Vulnerability context										
Weather-related shock	0.002	0.849	0.009	0.228	−0.041	0.347	0.021	0.687	**0.283**	**0.026**
Financial shock	**0.025**	**0.005**	**0.028**	**0.002**	0.039	0.364	−0.066	0.266	**0.208**	**0.045**
Constant	**0.535**	**0.000**	**0.296**	**0.009**	−1.101	0.129	−0.296	0.676	**2.255**	**0.097**

Significance of bold values < 0.1; R^2: 0.25 (Equation 1), 0.21 (Equation 2), 0.11 (Equation 3), 0.14 (Equation 4), 0.18 (Equation 5).

wheat. This is also evident from **Figure 3**, which shows that the Simpson's Diversity Index increases as the number of introduced varieties that are adopted increases. However, the relation seems to change course when the number of varieties adopted is greater than six.

The positive and significant relation between diversification and the perceived change in rice and wheat yields is evident from Equations (3) and (4). For rice, the perceived yield increase is negatively associated with female heads of households. The perceived change in rice yield was positively influenced by the level of education of the household head, acres of land cultivated and the access to informal sources of credit. Perceived change in wheat yield is negatively associated with the presence of animals on the farm, measured in Tropical Livestock Units (TLUs).

Equation (5) analyses the influence of the perceived change in yield on the overall recovery capacity of the households. This relation is significant only for wheat, but not for rice. This result is probably due to the fact that the initiative's impact was lower for the latter crop, as previously indicated. The recovery capacity is even influenced by the social capital; explicitly it is positively related to female-headed households and negatively related to high levels of trust in people. Finally, it is possible to observe that the recovery capacity is positively linked to financial and weather-related shocks. These results highlight that a perceived increase in resilience occurs only if households have been exposed to shocks.

The system of equations demonstrates the consequentiality and causality of the relations between the outputs and outcomes of the initiative. Regression results provide evidence that: (a) the adoption of the varieties disseminated through S4N positively

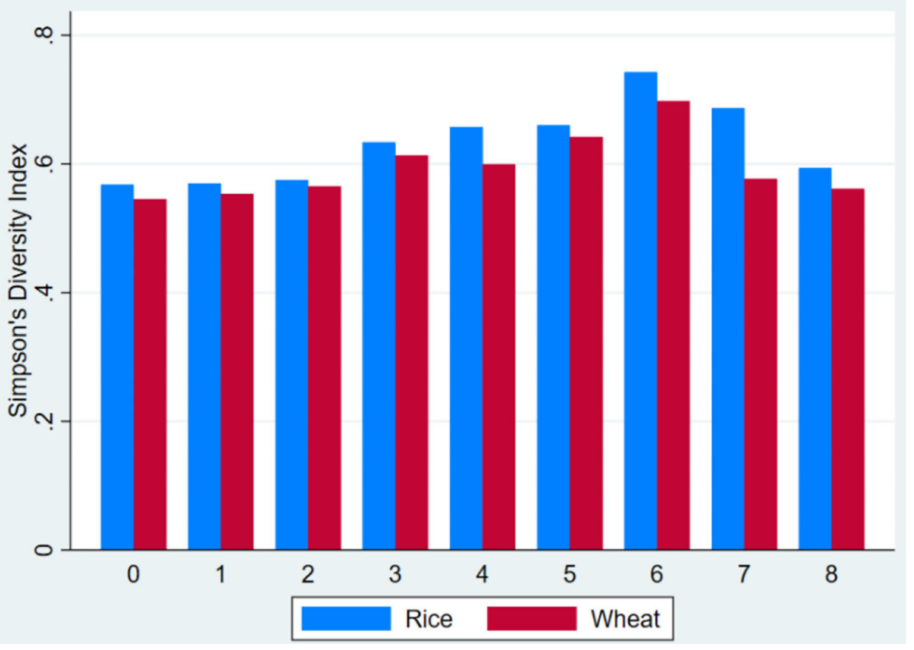

FIGURE 3 | Relations between the number of initiative-introduced rice and wheat varieties adopted by the household and varietal diversification of wheat and rice (Simpson's Diversity Index) (average per household).

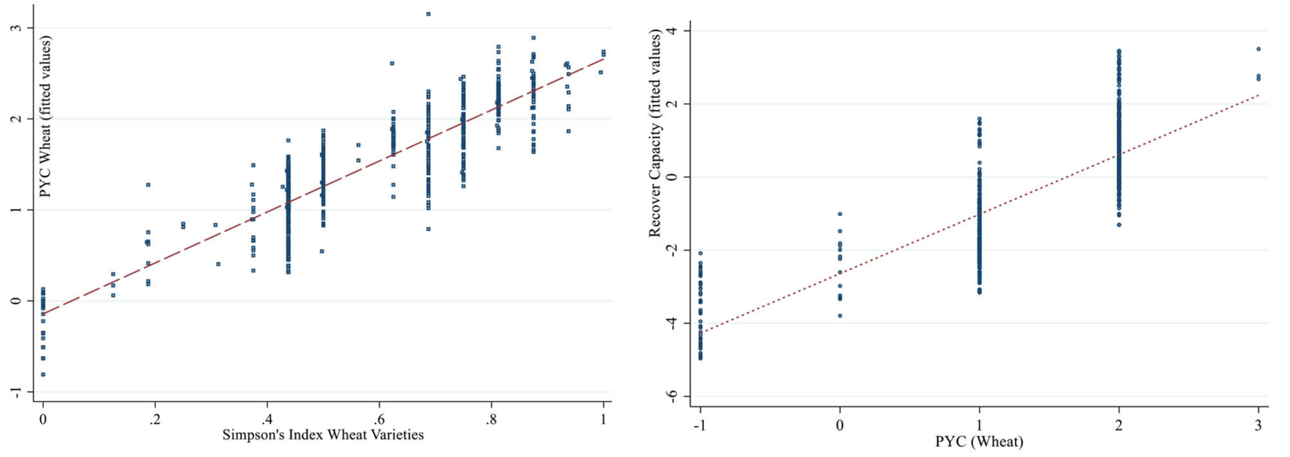

FIGURE 4 | Relation between observed *SDI* of wheat and the estimated *PYC* (left) and the relation between the observed *PYC* (wheat) and the estimated *RC* (right).

affects varietal diversity of rice and wheat (Equations 1, 2); (b) a more diversified production has in turn positively influenced the perceived changes of the yield of the two crops (Equations 3, 4); and lastly, the improved wheat yield trends have enhanced overall recovery capacity of the households from agricultural shocks (Equation 5). **Figure 4** helps us to understand in more detail the relation between the observed level of wheat diversification and the estimated perceived wheat yield trend (left panel) and the relation between the latter and the estimated overall recovery capacity of households (right panel). A Simpson's Diversity Index of 0.8 is associated with a perceived increase in wheat yield of over 50% (left panel), that in turn is linked to positive levels of the household's recovery capacity (right panel).

Finally, we analyse whether the estimated relationships and effects of the change in the institutional context are the same for all the households or whether they may vary according to the initial level of outcomes and output characterizing each household. For instance, it could be desirable for positive effects

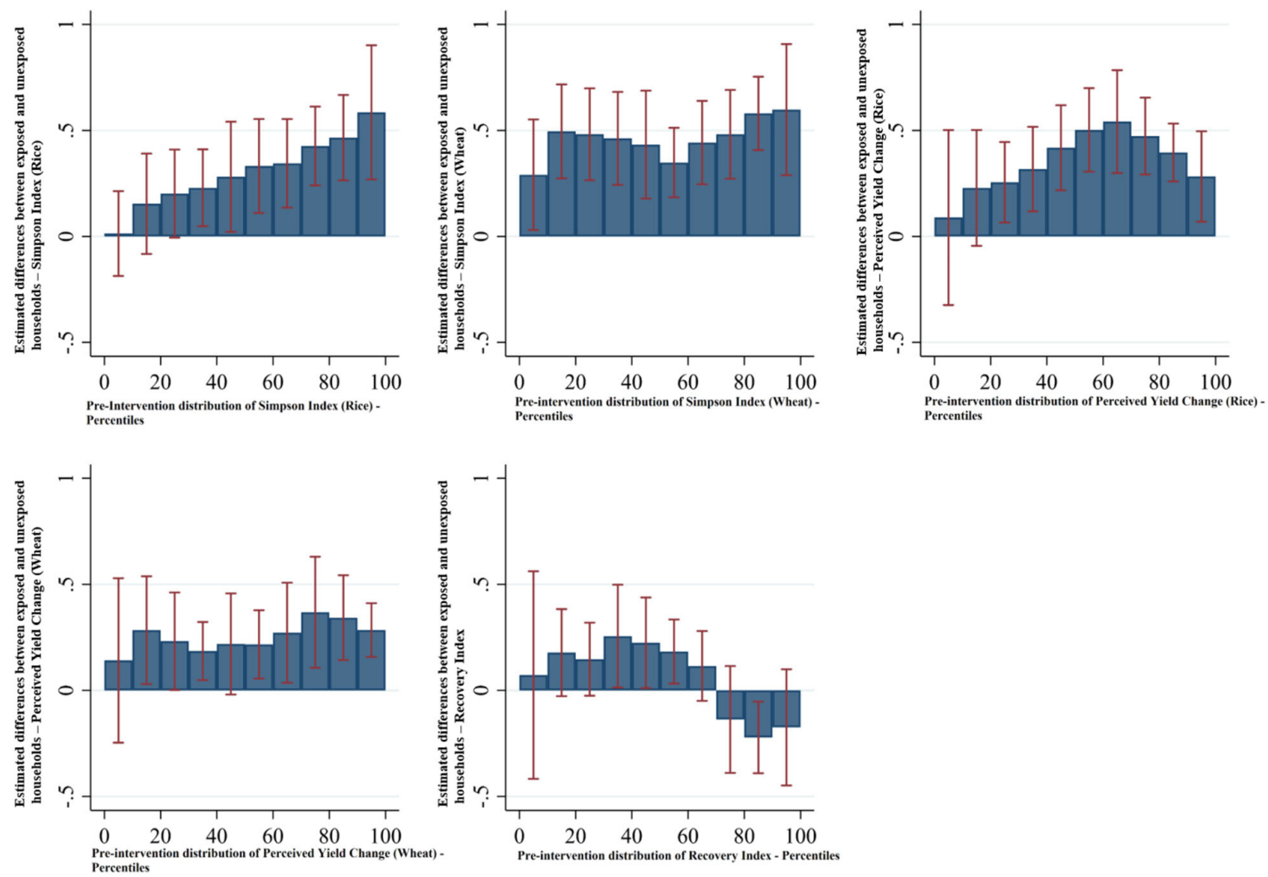

FIGURE 5 | Average differences between exposed and non-exposed groups across percentiles of the distribution of the pre-intervention value of the respective variable. For comparative purposes, outcomes are expressed as standardized values (mean = 0 and standard deviation = 1).

to be larger for the households that need more assistance than others. **Figure 5** reports the estimated differences of percentiles for each of the five outputs and outcomes of the intervention between exposed and unexposed households, as predicted by the system of equations. Again, it is clear that household exposure to the initiative significantly increases the intra-species diversity of wheat and rice on farm. For rice, the exposure to the initiative has an effect on diversification that is proportional to the prior level of rice diversification of households. For wheat, however, the effect is not sensitive to the level of diversification. When observing the impact on the perceived yields, similar patterns can be identified: the effects on wheat productivity are positive and similar across percentiles, while they can vary significantly across percentiles in rice, suggesting an inverse U-shaped relationship between rice productivity and the benefits provided by exposure to the initiative. Finally, the change in the institutional context is beneficial to the most of the households' ability to recover from agricultural shocks, benefitting, in particular, those households that, being at lower percentiles for the recovery index, are more vulnerable.

DISCUSSION

It is acknowledged that the use of a diverse set of two or more crop varieties in the field can help the farming system to buffer against adverse environmental conditions. Different studies analyzed the benefits generated by a varietal diversification mainly through experimental trials under controlled conditions or through observational studies of existing systems (Sukcharoen and Leatham, 2016; Nankya et al., 2017). These studies strongly suggested that varietal diversification can be an effective strategy, but do not provide empirical evidence on actual interventions. The current study provides this evidence on livelihood benefits stemming from the implementation of a strategy focused on varietal diversification through the analysis of the effects of the largest intervention so far based on citizen science: the Seeds for Needs initiative.

DR estimator results indicated that exposure to initiative activities generated positive and significative changes on the variety portfolio of smallholder farmers of the target crops, rice and wheat. Moreover, the DR results confirmed the research hypothesis underpinning the overall study, namely that exposed households can obtain substantial livelihood benefits in terms of increased crop productivity and improved ability to recover from shocks. In accordance with the findings of Joshi et al. (1997) and Gotor et al. (2017), outcomes of the current empirical analysis highlight the effectiveness of development programmes aimed at strengthening rural livelihoods through participatory approaches and use of local agrobiodiversity.

The second empirical analysis (system of simultaneous equations) identified strong causal linkages between households' exposure to the S4N activities and increased varietal diversification of farms and livelihood benefits. As shown by van Etten et al. (2019), access to crop varietal diversity through crowdsourced citizen science overcomes the lack of capital and knowledge of Indian farmers and provides a unique opportunity for them to evaluate and identify varieties that better adapt to the local context. This, in turn, stimulates farmers to adopt varietal diversification as a livelihood strategy. They will then use these varieties in their production fields to boost yields and improve households' recovery ability. Results are in line with previous studies that pinpoint varietal richness as an effective strategy capable of guaranteeing a more stable average yield and beneficial effects on crop productivity (Kiær et al., 2009; Nalley and Barkley, 2010; Sukcharoen and Leatham, 2016), as well as making farming systems more resilient and less vulnerable to weather disturbances (Akem et al., 2000; Mulumba et al., 2012).

Interestingly, the results highlight contrasting effects generated by livelihood assets on livelihood strategies and livelihood outcomes. Consistently with previous studies (i.e., Deressa et al., 2009; Bahinipati and Venkatachalam, 2015; Malaiarasan et al., 2021), the current study shows that the presence of animals on the farm (physical capital), the extension of cultivated land (natural capital) and the access to informal sources of credit (financial capital) positively influence the adoption of a strategy focused on varietal diversification of rice and wheat, although the effect of these assets is negative on the yield change (livelihood outcome). Female-headed households are less likely to increase genetic diversity of rice in their fields, in fact they are associated with negative yield changes, even if they show positive levels of recovery capacity. This could be related to the fact that in Bihar (and India in general) women tend to be excluded from agricultural work due to socio-cultural restrictions (Government of Bihar, 2020). However, despite the pronounced gender gap, female-headed households seem able to act on other forces that allow them to increase their household's resilience from unpredictable agricultural shocks.

We also showed how the benefits were distributed according to pre-intervention levels. For wheat, the results were more encouraging than for rice, as wheat diversification and yield increases were insensitive to prior levels, while rice diversification and yield increases benefitted those households with lower prior levels. However, the intervention influenced the ability to recover from shocks that was largest for households that had intermediate prior levels of shock recovery ability. The most vulnerable households, which are at lower percentiles for the recovery index, also benefitted. Unexpectedly, the results of the analysis indicate that exposure to the initiative had a negative effect on the ability to recover from agricultural shocks for households with high prior levels, indicating some degree of increased risk for the less vulnerable households.

LIMITATIONS OF THE STUDY

This study is not exempt of limitations. The main one is that although the SRL framework assumes that changes in the institutional context can affect livelihood outcomes in two ways, we analyzed only the pathway from institutional change via livelihood strategies to livelihood outcomes. Moreover, only the existence of linear relationships within the SRL framework has been tested, while other livelihood outcomes could be included in the analysis. Furthermore, this study does not provide a detailed understanding of the distribution of the effects generated by the S4N initiative. Indeed, we do not have a plausible explanation for the different distribution of benefits between rice and wheat: surely, it will be important to target interventions in such a way that the most vulnerable households benefit as much as possible. Also, information generated by crowdsourced citizen science is especially rich and could be connected in more direct ways to the econometric analysis. For example, some varieties could have a larger effect on the reduction of vulnerability than others. Further research could improve the methodological approach of the current analysis by adopting a qualitative approach in order to better understand the relationships and interactions between the different domains of the SRL framework or by refining and outspreading the range of livelihood outcomes that could be pursued by the households and drilling down on more detail the effects generated by the intervention. Future interventions could benefit from better understanding the way in which the benefits of the intervention are distributed across households. This could in turn provide information to better target the range of varieties offered to farmers in diversification interventions.

CONCLUSIONS

The purpose of this study was two-fold: (1) to analyse the effects of the largest citizen science-based intervention to date, the S4N initiative that took place in Bihar, India from 2010 to 2017 and focused on rice and wheat cultivations; and (2) to provide evidence on the consequentiality and causality of the relationships between the outputs and outcomes of the initiative, following the sustainable rural livelihoods (SRL) framework. For this purpose, we implemented the RHoMIs as a survey instrument on 600 rural households in three districts of Bihar and we used the sustainable rural livelihoods (SRL) framework to understand the potential multiple interactions that are activated within the system by the intervention.

The quantitative analysis of this study provides evidence that exposure to the initiative's activities generated positive and significative changes on the variety portfolio of smallholder farmers. In turn, an increase in varietal diversification produced substantial livelihood benefits in terms of crop productivity, as well as strengthening the ability of households to recover from the unpredictable shocks associated with agricultural production. Furthermore, the analysis highlights the effectiveness of development programmes aimed at strengthening rural livelihoods through participatory approaches and use of local crop varietal diversity.

These findings are not surprising, as the initiative under analysis was explicitly designed to promote the conservation and use of a wider variety of rice and wheat by exposed farmers. However, it is important to understand the magnitude of its effects and its statistical validation. Moreover, these findings can be considered in order to offer useful insights about the effectiveness of different initiatives to policymakers.

We hope that the findings of this analysis can stimulate further research on knowledge transfer and will be used in programmes geared at reinforcing rural livelihoods through participatory approaches and use of local variety richness, while sustaining the conservation of important genetic resources. This is because rural households are the main custodians of intraspecific crop genetic variation, and they need to be recognized as such and supported in their efforts to conserve it for current and future use.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: Gotor et al. (2018).

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study. Informed consent was obtained from all subjects involved in the study. A written statement was read to the surveyed for their understanding and consent. As a non-clinical study, no ethical approval was required from national authorities or Bioversity International at the time of the execution of the field survey.

AUTHOR CONTRIBUTIONS

All authors contributed to the writing and review of the manuscript, read, and approved the submitted version.

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APPENDIX

TABLE A1 | Results of the exposure equation (Probit model).

	Coeff.	SE	*t*-stat	*p*-value
Human capital				
Age of household head	0.008	0.005	1.56	0.120
Education of household head	0.084	0.042	2.00	0.046
Household size	0.027	0.020	1.31	0.192
Social capital				
Gender of household head	0.399	0.157	2.54	0.011
Trust in people	0.862	0.175	4.94	0.000
Trust and cooperation community	0.249	0.103	2.42	0.016
Natural capital				
Land cultivated	−0.007	0.007	-1.12	0.262
Physical capital				
Inputs	−0.408	0.145	-2.81	0.005
TLU	−0.193	0.066	-2.93	0.003
Financial capital				
Off-farm Income	−0.193	0.166	-1.16	0.245
Debt	0.287	0.116	2.49	0.013
Formal credit	0.762	0.318	2.40	0.017
Informal credit	1.019	0.344	2.96	0.003
Vulnerability context				
Weather-related shock	−0.104	0.058	-1.79	0.073
Financial shock	0.155	0.060	2.60	0.009
Constant	0.488	0.882	0.55	0.580

Obs. 600, χ^2*: 127.6, Pseudo* R^2*: 0.153.*

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Data Collection Smart and Simple: Evaluation and Metanalysis of Call Data From Studies Applying the 5Q Approach

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Agricultural development projects often struggle to show impact because they lack agile and cost-effective data collection tools and approaches. Due to the lack of real-time feedback data, they are not responsive to emerging opportunities during project implementation and often miss the needs of beneficiaries. This study evaluates the application of the 5Q approach (5Q). It shows findings from analyzing more than 37,000 call log records from studies among five countries. Results show that response rate and completion status for interactive voice response (IVR) surveys vary between countries, survey types, and survey topics. The complexity of question trees, the number of question blocks in a tree, and the total call duration are relevant parameters to improve response and survey completion rate. One of the main advantages of IVR surveys is low cost and time efficiency. The total cost for operating 1,000 calls of 5 min each in five countries was 1,600 USD. To take full advantage of 5Q, questions and question-logic trees must follow the principle of keeping surveys smart and simple and aligned to the project's theory of change and research questions. Lessons learned from operating the IVR surveys in five countries show that the response rate improves through quality control of the phone contact database, using a larger pool of phone numbers to reach the desired target response rate, and using project communication channels to announce the IVR surveys. Among other things, the respondent's first impression is decisive. Thus, the introduction and the consent request largely determine the response and completion rate.

Keywords: digital agriculture, ICT, IVR, interactive voice response, farmers feedback, two-way communication, 5Q approach

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INTRODUCTION

Digitalization as a socio-technical process has become a transformative force to applying digital innovation to agriculture and food systems (Klerkx et al., 2019). However, it raises the question: can smallholders keep up the pace and benefit from the intended transformation? Collaborations between national actors from agricultural institutions and the research body to apply data-driven approaches can make farming more productive for smallholders (Jiménez et al., 2019), increase their net farm income, and transform food systems toward sustainability (Chapman et al., 2021). Digitalization initiatives promise improvements for smallholders in low- and middle-income countries (LMICs). Still, they do not reach a significant number of farmers. However, some of these initiatives have made progress in recent years (Baumüller, 2017), but barriers exist and need to be addressed. The main barriers are lack of technical infrastructure (Mehrabi et al., 2020), lack of access to digital tools and services, lack of ease of use for non-tech-savvy farmers, and lack of design that is targeted for low-literate and marginal groups. Recent studies show that mobile phone-based dissemination of information as a service for smallholders can have a positive impact in promoting farm management practices (Djido et al., 2021), deliver advice as an automated advisory service that collects household data to improve advice over time (Steinke et al., 2019), and use of speech-based services as a viable way for providing information to low-literate farmers (Qasim et al., 2021). The access and availability gaps and challenges with technology (e.g., lack of connectivity in rural areas) will disappear over time.

For this reason, socio-ethical barriers are the main barriers to overcome (Shepherd et al., 2020). Moreover, precisely because of the transformative momentum of digitalization, there is a risk for smallholders to enter the digital divide and power asymmetry gap. The risk is increased when digital technologies are embedded in the science community, private sector, and larger farms only. Smallholders are left behind in a big data divide (Carbonell, 2016).

The use of data-oriented tools in agriculture research has increased over the last few years. An important task of science is to support the design of new tools and services, evidence the use of digital tools by smallholders, and observe unintended consequences (Shepherd et al., 2020), especially for smallholders on the brink of the digital divide (May, 2012). Investment in last-mile infrastructure, universal access to information and data (Mehrabi et al., 2020), and out-of-the-box interoperable systems (Kruize et al., 2016) are important research areas for coming years. Transforming research toward more agile data collection, using IVR, an automated phone system using recorded messages that allows callers to interact with the system without speaking to an agent, as a medium to reach people in LMICs, and overcome language and literacy barriers has become relevant recently. Advantages of IVR compared to other communication channels, e.g., text message services, mobile phone applications, radio programs, among others, are factually precise; voice messages can be recorded in different local languages and accessed on-demand, and farmers can easily follow the voice message even if they do not know how to read. For scientists, the advantages are more cost-effective data collection since operating mobile phone calls is usually cheap and produces ready-to-analyze data in near real-time because being stored just-in-time while operating the call in cloud storage.

IVR has been used for a longer time in health applications, and research on response rates in LMICs has been done for health risk prevention. Global data of IVR response rates in health research shows between 30 and 50% (Gibson et al., 2019; Pariyo et al., 2019). Experiences in using IVR for health in Ghana and Uganda showed positive attitudes toward IVR by respondents and constant response rates over a more extended time (L'Engle et al., 2018; Byonanebye et al., 2021). The ease of use, empathy, trust in information source, cultural and language factors, availability and accessibility, reduced costs, and women's empowerment supports the willingness to use IVR systems. On the other hand, the barriers to use are lack of human interaction, the complexity of information, and facilitating conditions, especially lack of technical infrastructure (Brinkel et al., 2017).

The above arguments suggest that science should experiment and pilot new digital tools to provide inclusive two-way communication channels that include smallholders by overcoming the digital divide's burden and bringing to life transdisciplinary research initiatives that include all food system stakeholders. In traditional, non-digital participatory research, the leading farmers' barrier to participation is not having a voice to communicate needs. At the same time, using translational research, scientists work on digital solutions to use science for applicable digital solutions to improve agricultural productivity (Passioura, 2020). However, two-way communication in participatory processes has been used in the past successfully, for example, to understand the vulnerability context of farmers in value chains (Valdivia et al., 2014), or the use of the power of crowdsourcing to significantly improve the data basis for algorithm training (Hampf et al., 2021).

This paper presents the details of evaluating 5Q, a concept of keeping data collection smart and simple by asking five thoughtful questions, combined with IVR for agile data collection, developed to effectively collect feedback from agricultural development projects with a potential for massive data collection (Jarvis et al., 2015). Its principle is to incorporate feedback mechanisms in projects and build an evidence base that improves decision-making, adoption, and impact, keeping it smart, simple, and easy to use. This publication shows the iterative improvement of configurations and measures taken during individual studies in five countries and over six years of operating IVR survey campaign calls. The analysis processed 37'503 call metadata in 44 IVR call campaigns and five countries and provides insights into call status, average call duration, reached IVR blocks, and differences in response rate between different call types and survey topics.

The paper is structured as follows; first, it presents materials and methods on how call metadata were analyzed and evaluates the implementation of 5Q in nine studies in Tanzania, Uganda, and Rwanda in East Africa, Ghana in West Africa, and Colombia in South America. Second, the results from the analysis and evaluation are presented. Finally, findings are discussed, and future research needs are laid out in the discussion and conclusions.

MATERIALS AND METHODS

Call metadata were analyzed from 44 IVR call campaigns from nine studies in five countries between 2015 and 2021. The design of all campaigns followed the 5Q approach, which was first proposed by (Jarvis et al., 2015) as an agile data-oriented approach to incorporate feedback mechanisms in agricultural development projects.

Introduction to 5Q

5Q is a concept that uses the principle of keeping data collection smart and simple by asking five thoughtful questions in question-logic-trees in repeated cycles or rounds, and by using cost-effective digital communication tools for data collection. 5Q supports the idea that the adoption of new technologies or services is a process that goes through several stages (Glover et al., 2019). The recuring feedback loops can help to understand better how the technology fits into farmers' context, perceptions, barriers, and enablers for adoption. Besides more conventional variables such as farm characteristics and economic variables, the role of knowledge, perceptions, and attitudes as intrinsic factors toward adoption play a key role in farmers' decision-making process for adoption and use (Meijer et al., 2015). 5Q collects intrinsic factors in feedback loops from farmers as potential adopters to inform promoters and implementers, and sends information back to farmers. Thus, it moves from simply collecting data to using data for building evidence on knowledge (perception), attitudes, and skills for practice (KAS). The feedback loops can be embedded in a project monitoring and evaluation plan and used complementary to participatory tools and traditional data collection methods (**Figure 1**). As part of a two-way information flow strategy, feedback generation can start before defining a project's theory of change or research question by asking the potential benefiting community about their needs or specific barriers to adopt a new technology. During the implementation of project activities, the approach can be used to design a workflow of design feedback loops between implementers and beneficiaries. Nevertheless, most importantly, it provides recurring data for decision-making during project implementation and contributes to monitoring and evaluation outcomes. After a project ends, 5Q can be used to feed into an impact assessment study.

Smart Question Trees

5Q starts by identifying questions that respond to a research question or a project's theory of change. Questions can recall a farmers' perception, monitor the effects of implemented activities, or evaluate adoption, among others. Next, a logic-tree structure is used to define the sequence of the survey. Questions are linked in a tree structure by branches and decision nodes, connecting a respondent-based answer to the following questions block. A 5Q survey using a question-tree requests about five answers from a respondent within one survey round, depending on the respondent's pathway through the question-tree branches and nodes (**Figure 2**, left). At the end of each survey round, respondents can be grouped based on typologies from survey answers. The created groups can be used for tree variations for the next survey round (**Figure 2**, right).

Design of Survey Rounds

Survey rounds carried out in cycles during the implementation of projects provide feedback for decision-making, making the process responsive and effective, and ensuring mutual accountability and integration of stakeholders in the project implementation phase. Using 5Q suggests asking stakeholders more frequently about their needs and perceptions of activities carried out within a project; more specifically, it explores how the project can serve beneficiaries. For example, a survey round collects data from project beneficiaries about the usefulness of project activities. The collected data serve project implementers to make a corrective action on the project implementation process. A plan for survey rounds and sequential question trees can be designed at the beginning of a project and adjusted as new data are produced in each survey round.

Digital Communication Tools

Digital communication tools facilitate more cost-effective data collection than traditional approaches. Therefore, 5Q selects the most appropriate digital channel for the context of stakeholder groups. For example, on the one hand IVR calls are the most time- and cost-effective way of collecting data but are ineffective when a socio-cultural context or low literacy level is prevalent within stakeholders. On the other hand, survey interviews facilitated by hired enumerators or volunteer community members using mobile apps can overcome the literacy barrier but are less cost- and time-effective.

This study compared data from IVR survey calls only. Findings of comparing IVR data collection with mobile phone data collection can be found in Eitzinger et al. (2019).

Studies

Several studies used the 5Q to collect data or obtain feedback from farmers during project implementation. In **Table 1**, project goals were summarized, and the 5Q call campaigns were described.

The goal of the studies in the West Usambara Mountains in Tanzania and Northern Region of Uganda carried out between 2015 and 2017 was wide-scale adoption of climate-smart agriculture (CSA) among farmers through prioritizing practices and technologies (Mwongera et al., 2016) and demonstration of CSA practices in training sessions and farmer-managed demonstration plots. 5Q was applied to obtain farmers' feedback after implementing project activities. Using regular IVR survey calls, the adoption of practices were measured in the three levels of KAS. The studies in Colombia focused on better understanding farmers' perception of climate risks on agricultural livelihoods (Eitzinger et al., 2018) and farmers' perception of the seasonal weather forecast for Colombian maize and rice agriculture (Sotelo et al., 2020). In Ghana and Mount Elgon in Uganda, a project sought to ensure that farmers continue to invest in coffee and cocoa by breaking down recommended CSA practices into smaller, incremental investment steps (Jassogne et al., 2017). Likewise, in Tanzania and Uganda studies, KAS of farmers were queried for incremental steps for investing in CSA practices. In Rwanda, climate services were disseminated as participatory integrated climate services for agriculture, also known as the PICSA approach. Farmers in four provinces across Rwanda were trained to read weather forecasts related to an agricultural advisory. 5Q was used to collect farmers' feedback about climate services (Birachi et al., 2020). During the covid-19 pandemic, two surveys were implemented in Rwanda to collect information about the farmers' perceived impact on agricultural production and households' food security.

The contact database of respondents' phone numbers was provided in all studies by local partners, except in Tanzania, where the phone numbers were collected during a baseline

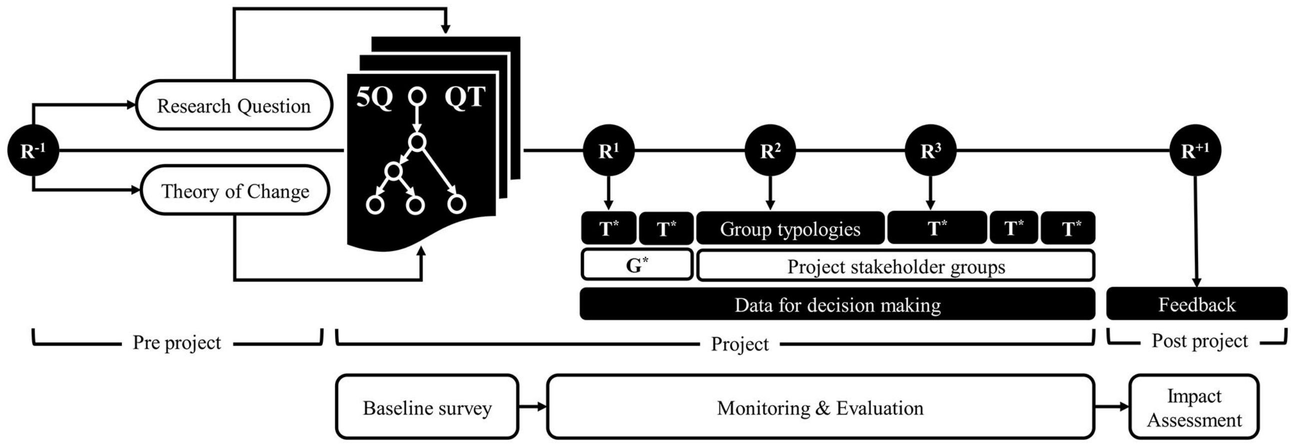

FIGURE 1 | 5Q embedded in a traditional project's data collection timeline (5Q components in shapes with black filled background). Symbols are question-tree QT, survey rounds R, stakeholder groups G, and group typologies T.

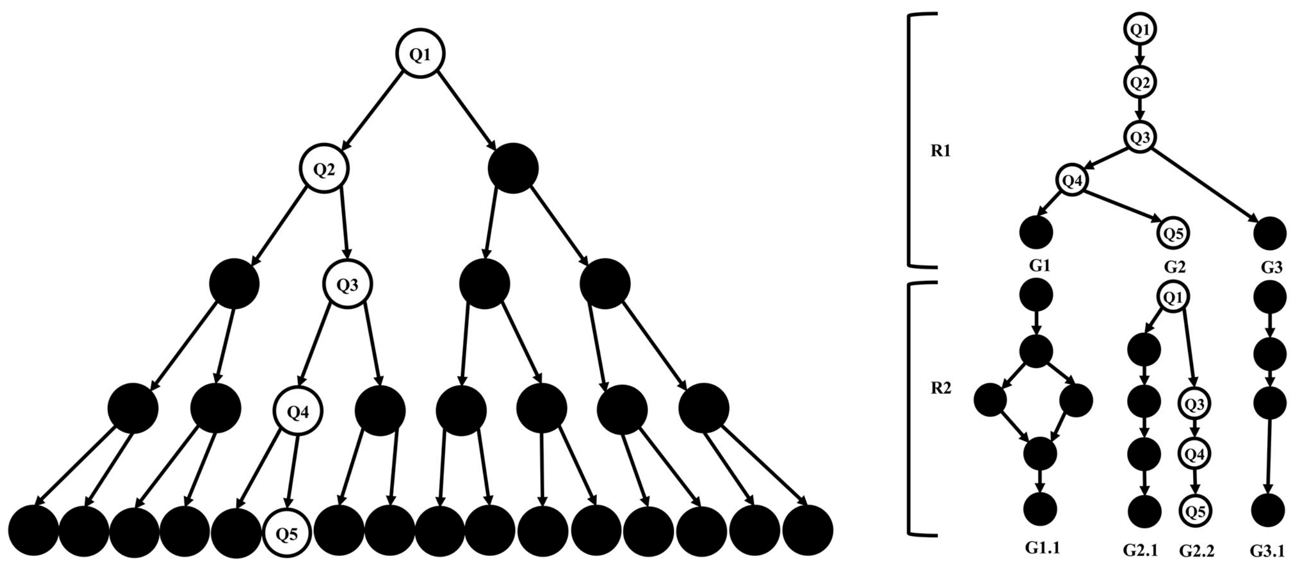

FIGURE 2 | Questions Q in a tree structure with branches and decision nodes (left) and survey rounds creating typology groups G for follow-up survey round R (right). Unfilled shapes show an example of a respondent's pathway in the tree structure.

interview. Results and data visualizations for all studies can be accessed on the 5Q results dashboard[1].

Metadata Analysis

Call metadata of 37'503 IVR calls were analyzed from 44 call campaigns among five countries. Three different call statuses were analyzed. Call status *complete* is used when a respondent reached one of the end blocks in a question tree during a call, *incomplete* when the respondent responded to some of the question blocks but did not reach the end block and *failed* when the respondent did not respond to the call until the maximum number of repetitions was reached defined by the call campaign configuration. For all call campaigns, default call configurations were used, as a defined call time window between seven in the morning until eight at night, repeat settings of two intentions in quick successions of five min, and repetitions up to two times every hour; on detection of a voice mail, the call intention was stopped until the next programmed repetition. Question tree complexity was defined as the number of blocks (questions) reached during a call. Call duration was measured in seconds, and its relations to call status and reached blocks were analyzed.

Further, call metadata were examined if the percentage of completed calls depends on the call type or topic. Different call types were introduced as voice message calls to obtain the respondent's consent, feedback surveys,

[1]https://5qapproach.org/dashboard/index.html

TABLE 1 | Projects using 5Q combined with IVR survey campaigns.

Country, Region	Year	Project goal	Topic	Type of data collection	Contact database	Call series number	Calls	Average call duration (s)
Tanzania, West Usambara Mountains	2015	Farmers' adoption of climate-smart agriculture practices	CSA	Feedback KAS	439 farmers registered during household visits	1 to 16	1,424	68
		Farmer's improved knowledge on crop management	CM	Feedback after capacity building event	29 farmers registered during event	17	29	137
Colombia, Cauca	2016	Improve farmers' understanding of weather forecasts	CS	Perceptions on Climate Services	146 farmer contacts shared by partner	18 to 19	102	129
		Understanding of farmers' perceptions of climate risks	CR	Perceptions on climate risks	1,240 farmer contacts shared by partner	20 to 22	2,183	95
Colombia, Cauca	2017	Monitoring and evaluation of CSA effects on household level	CSA	Household Survey	127 from project implementer	23 to 38	1,155	73
Uganda, Northern Region	2017	Farmers' adoption of climate-smart agriculture practices	CSA	Feedback KAS	215 farmers registered during household visits	39 to 42	664	53
Uganda, Mount Elgon	2019	Farmers adopt a stepwise approach for climate-smart investment pathways	CSA	Feedback KAS	2,361 farmer contacts shared by partner	43 to 63	2,592	102
Uganda, Bushenyi					580 farmer contacts shared by partner	64 to 70	1,305	105
Uganda, Mount Elgon	2020	Farmers adopt a stepwise approach for climate-smart investment pathways	CSA	Feedback KAS	2,361 farmer contacts shared by partner	71 to 84	5,915	197
Ghana, Western Region	2019	Farmers' adoption of climate-smart agriculture practices combined with climate services	CSA, CS	Feedback KAS	512 farmer contacts shared by partner	85 to 88	698	344
	2020	Farmers' adoption of climate-smart agriculture practices combined with climate services	CSA, CS	Feedback KAS, perceptions	302 farmer contacts shared by partner	89 to 90	432	237
Rwanda	2019	Participatory Integrated Climate Services	TRAIN CS	Trainings call	74 contacts shared by partner	91	72	149
				Stakeholder feedback		92	70	135
			TRAIN	Trainings call	10,998 farmer contacts shared by partner	93	5,330	171
			CS	Farmer feedback	5,330 completed trainings call	94	4,763	188
	2020	Impact of covid-19 on agricultural production	INTRO	Introduction voice message	4,763 confirmed consents	95	4,018	47
			COVID	Perceptions on covid-19 impact	4,018 confirmed consents	96 to 98	6,653	198
	2021	Participatory Integrated Climate Services	INTRO, TRAIN	Introduction and Trainings call	5,330 completed trainings call	99	3,328	14
			CS	Farmer feedback	3,328 confirmed consents	100	3,328	218
				Stakeholder feedback	74 contacts shared by partner	101	57	129
		Impact of covid-19 on agricultural production	COVID	Perceptions on covid-19 impact	5,330 completed trainings call	102	4,006	268

recall a respondent's perceptions, and collecting survey data. Responses from farmers and other project stakeholders were examined separately. Finally, differences in the distribution of call status percentages with the call or survey topic were analyzed. Earlier call campaign types were related to climate change research. More recent campaigns focused on the impact of covid-19 on agriculture production and food security.

Evaluate 5Q and IVR Call Campaign Setup

The paper evaluates how 5Q has been implemented in the different studies and reviews the configurations and measures taken during the individual studies for the operation of campaign calls to improve the response rate. The measures have evolved and have not been tested in an experimental setup. However, lessons learned from call campaign configurations have been implemented incrementally as new campaigns were started. Most relevant learnings were listed, and further details were provided on how the question trees were developed with project teams in the different countries.

RESULTS

Metadata Analysis of IVR Survey Call Campaigns

Metadata analysis of 44 call campaigns shows that response rate and call completion status for IVR survey calls varies between countries, survey types, and research topics (**Figures 3**, **5**). The overall response rate was highest (farmer picked up the call and stayed until the first block) in Colombia with 95%, followed by Rwanda with 78%. In Colombia, however, only 18% finished all blocks and reached a call status completed. In comparison, in Rwanda, the rate of call completion was higher, with 38%. Response rate and calls status distribution were similar in Uganda and Ghana, 57% response rate in Uganda, and 46% in Ghana. Call metadata from Tanzania show the lowest rate of completed calls (16%). However, Tanzania ranks before Ghana when combined with incomplete calls (see **Figure 3**, left). At the sub-national level, differences can be found in Uganda. Response rate and survey completion were lower in Nwoya (6%) and Bushenyi (16%) than 27% completed surveys in Mount Elgon. Also, results from Colombia show differences between Cauca and the two other Colombian regions (**Figure 3**, right).

Figure 4 shows the response rate and call completion for each call series operated between 2015 and 2021 across the five countries (see **Table 1** to identify the call-series number in the x-axis). A higher percentage as the countries average for completed surveys can be observed for the call series 52, 53, 58–61, 78, and 82–84 (feedback KAS) in Mount Elgon, Uganda. For Rwanda, the call series 93 (IVR training call for farmers), 95 and 99 (voice message introduction), and 96 (the first covid-19 call) show higher rates than the average rate of completed surveys. In Colombia, the call campaigns 20 and 21 (collecting perceptions on climate risks) and 18 and 19 (feedback on climate services) had higher percentages of complete calls than other call campaigns. The series 25 in Colombia had high completion rates because it was an introduction voice message, and call campaign 34 is an outlier ($n = 7$ calls only) and is therefore not a representative call metadata. The first call campaigns in Tanzania (series 1 to 7) were not included in the country average. During this first call campaigns in Tanzania, some calls had technical issues and did not show any calls with status completed in the data. However, higher rates than the average of completed surveys for Tanzania were achieved in one of the KAS feedback surveys (12) and the feedback call after the capacity-building event for crop management (17). Ghana showed a similar response rate across all call campaigns with the highest response rate of 32% on the call series (89).

Comparing the different survey types and research topics that used 5Q and IVR for data collection shows that, as already observed in **Figure 4**, introduction voice messages (INTRO), training calls (TRAIN), and calls on perceptions can achieve higher rates of completion (**Figure 5**, left). In addition, research on covid-19, crop management, and climate services show higher percentages on complete call status than others (**Figure 5**, right).

Figure 6 shows the given consent (yes) or (no) by the same respondent in Rwanda to different calls and times. The two call campaigns about feedback on climate services in 2019 and 2021 had overall lower agreement rates than the two covid-19 calls in 2020 and 2021, even though the two calls in the year 2021 were carried out within a time window of two weeks (the CS2021 was carried out in March and the COVID2021 in the first week of April with the same sample population).

The average call duration compared to call status and reached blocks is compared in **Figure 7**. Since incomplete calls can still provide valuable data, it is essential to understand how much time and reached blocks the respondent's stays in the call. When comparing the two graphs call status complete (left) and incomplete (right), most data in Ghana (blue squares) are yielded from complete calls (the maximum number of reached blocks was 20). The same effect can be observed for the Uganda data (black flipped square). Most calls stop between 20 and 30 blocks, including both complete and incomplete calls. For Rwanda, a drop can be observed after 30 blocks. Since incomplete calls can still provide valuable data, it is essential to understand how much time and reached blocks the respondent's stays in the call.

Lessons Learned From Using 5Q and IVR

Developing Question Trees and 5Q Implementation Plan

Using 5Q and IVR is a cost-efficient way of collecting feedback for an agricultural development project. It works best when question-logic trees and survey rounds align with the project's theory of change and research questions, being developed in a collaboration between various project members. The studies in Tanzania, Rwanda, and Colombia developed the question-logic trees in workshops lasting several days. In Ghana and Uganda, they were developed in virtual meetings.

When designing the questions and surveys, usually researchers and project implementers want to include many questions. The role of the researcher leading the 5Q component is to remind the group of the 5Q principles, which are, keep it smart and simple. The group needs to mind that 5Q will not replace any of the other data collection components of the project, such as baseline surveys gathering information to characterize the project's beneficiaries. The type of questions that should be considered for a 5Q question tree is closer to polls, where people's choices and understanding of their opinion, perception, understanding what works for them within the project's theory of change.

Once the question trees, logic, and rounds were defined in each project, the next step was preparing the scripts for

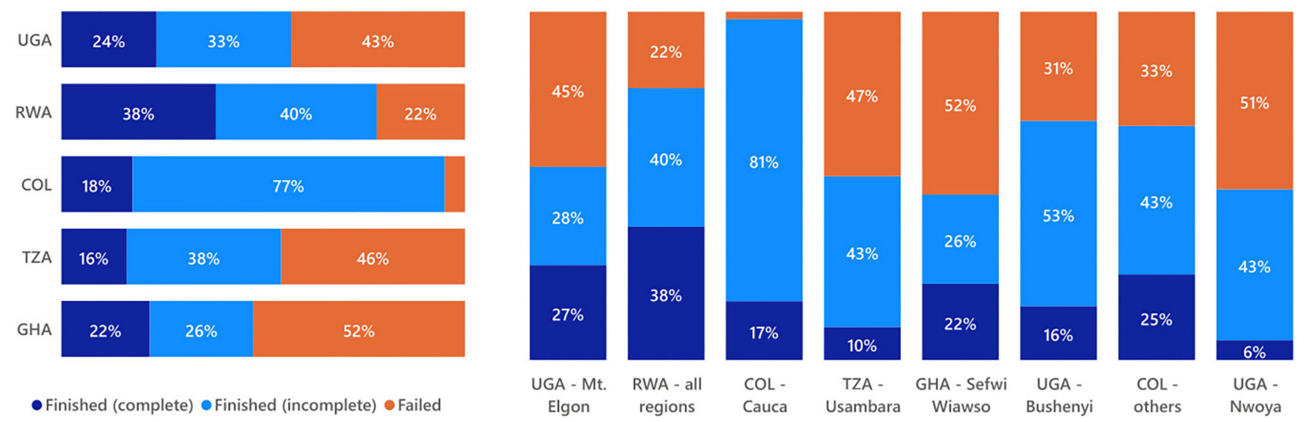

FIGURE 3 | Call status per country (left), and regions per country (right).

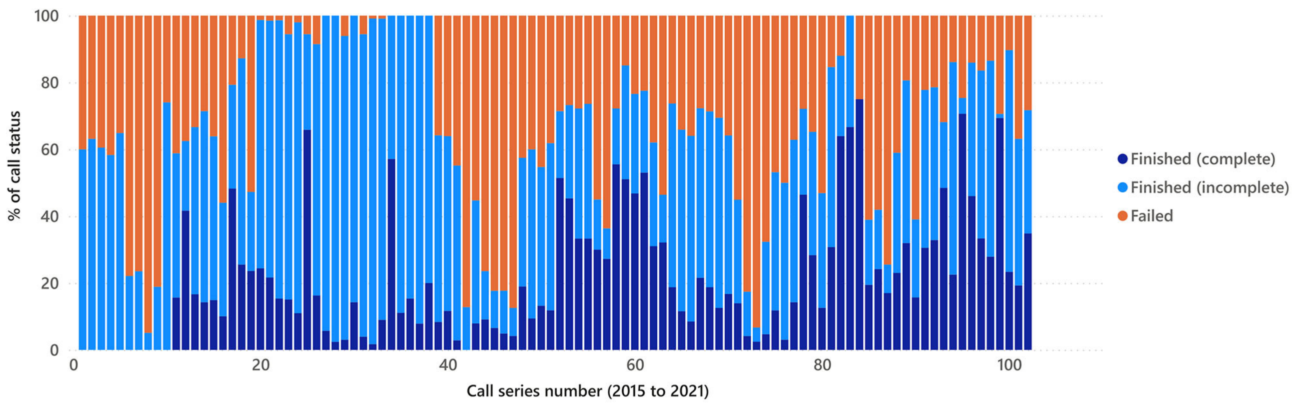

FIGURE 4 | Call status per series of calls, including the number of reached blocks per call.

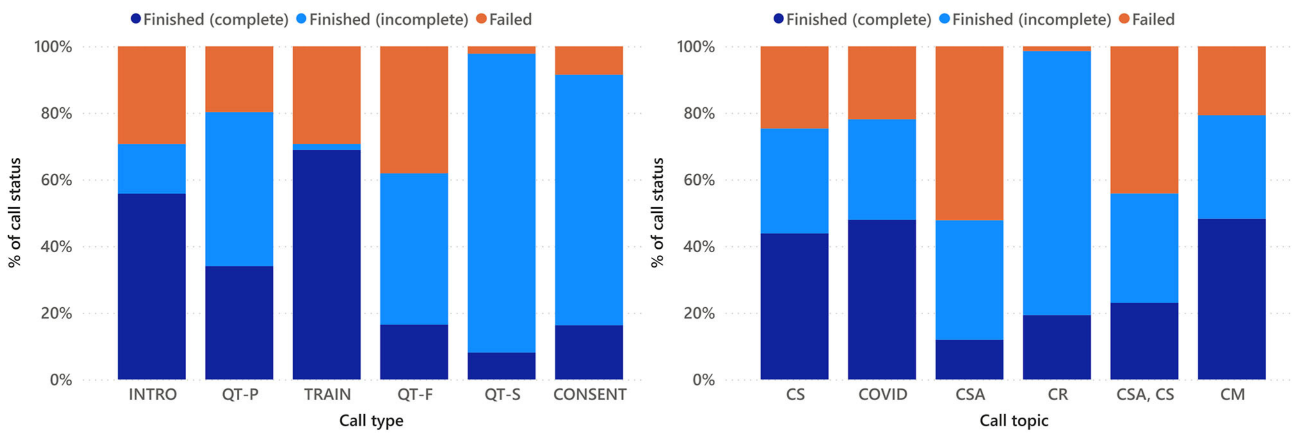

FIGURE 5 | Call status per survey type (left) and survey topic (right). Different survey types are one-block (listen-only) voice messages (INTRO), multi-block question-trees on perceptions (QT-P), feedback (QT-F) and surveys (QT-S), initial calls for obtaining the respondent's consent (CONSENT), and test- and training calls (TRAIN). Topics included calls about climate services (CS), impacts from the covid-19 pandemic (COVID), climate-smart agriculture (CSA), climate risks (CR), crop management (CM), and combinations.

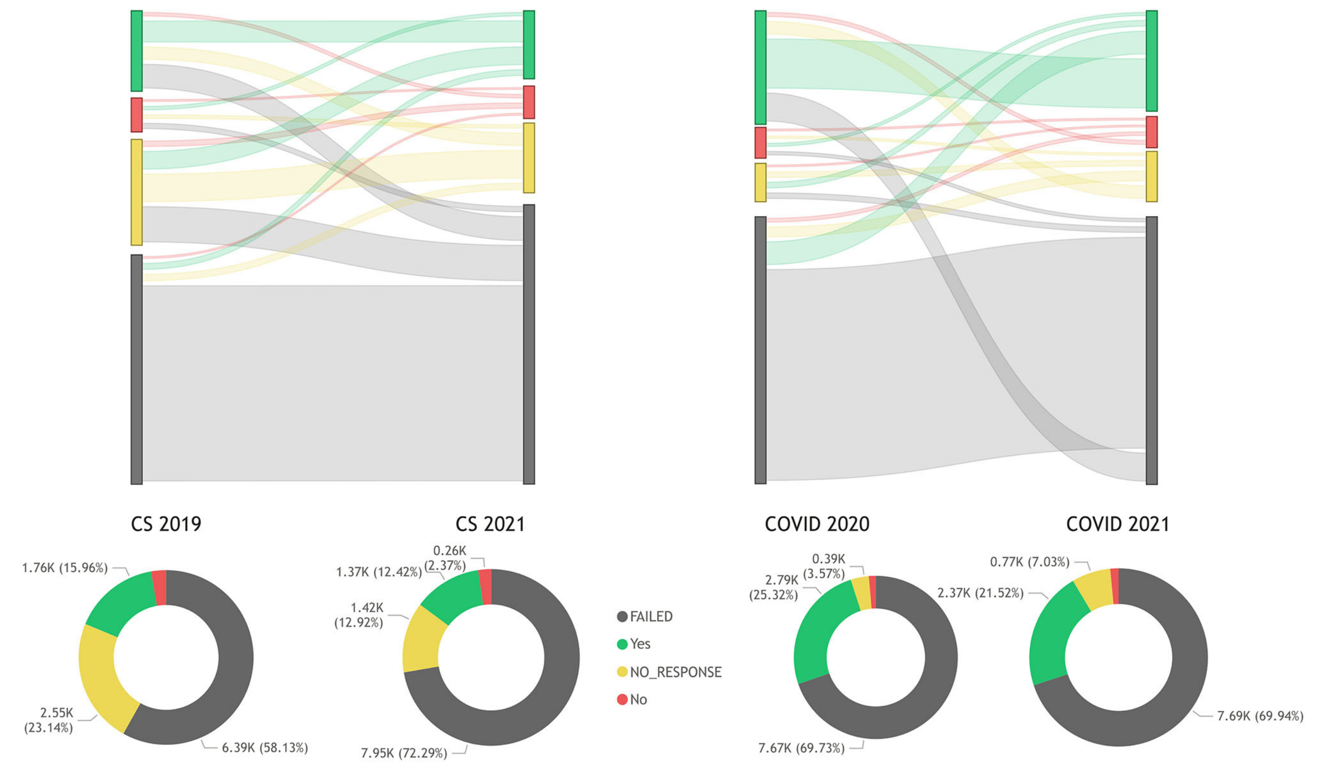

FIGURE 6 | Respondent's consent (first block of QT) changes between the first and second call round for climate services CS topic (left) and covid-19 COVID topic (right).

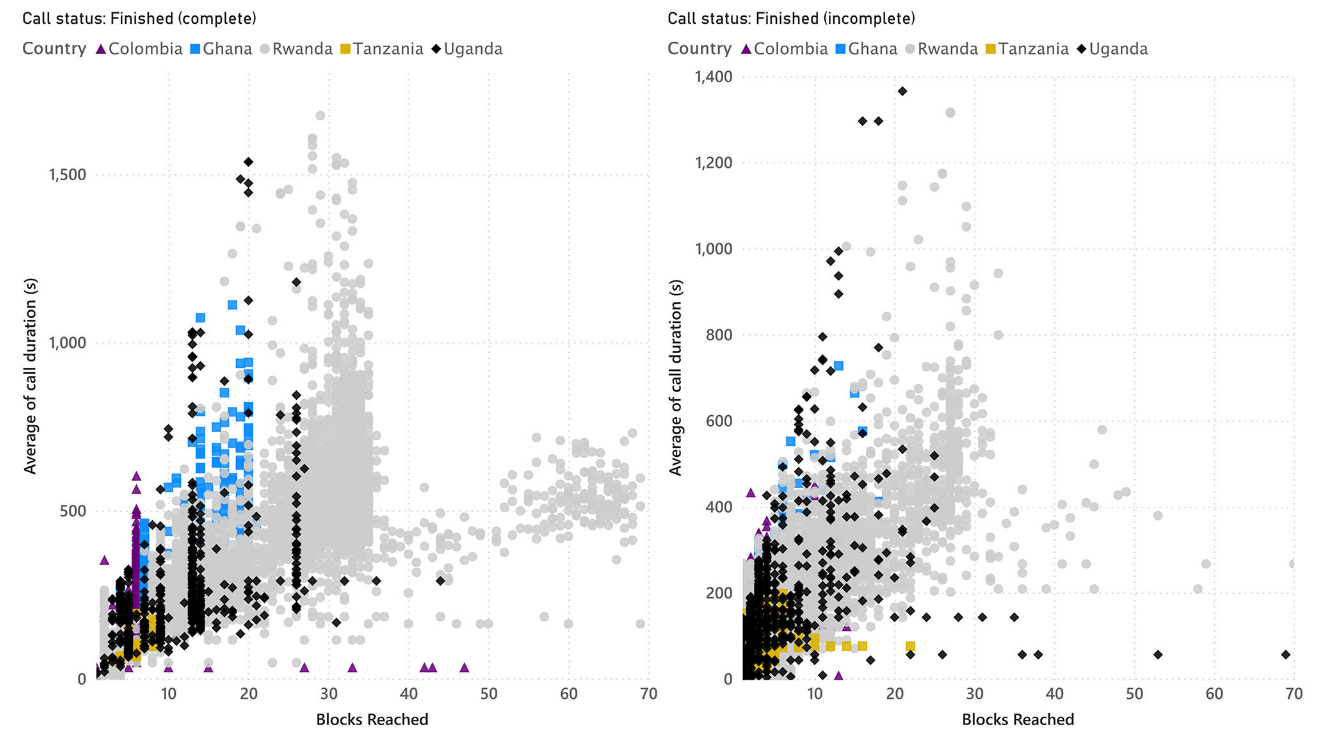

FIGURE 7 | Blocks reached an average of call duration by call duration and country; calls complete (left) and incomplete (right).

each planned call. The script is an essential link for the call operations, often carried out by a technical operator unfamiliar with the project itself. Thus, it is crucial to have a consistent self-explaining script to facilitate the process. The script includes the spoken text that needs to be recorded for each question (block in the call campaign) and any additional language. In addition, the script should indicate the linkages between question-blocks and, at best, include a drawing of the tree structure (see **Figure 2**). The script's best works in a table format, using the following columns: Block number | Question code | Goto code | Transcript | Translation [n] | Audio filename.

Operation of IVR Call Campaigns

The selection of the IVR systems should be made based on the capacity of the project, and there are several options. One option is to set up the IVR system on a server using application programming interfaces (API) from an IVR service provider. Another option is using a programmable voice cloud platform from a communications platform provider. The latter option needs less in-house technical expertise and provides a global range through a single service provider. Therefore, it can be more cost-effective when running call campaigns in several countries and with fewer respondents, like in some of the presented studies in this paper. In the case of operating in one country, partnering with a local telecom provider might be a better option.

Before starting the first call campaign, the contact database of respondents' phone numbers is required. In most cases, it should come from the project consortium. In most studies (see **Table 1**), the implementation of IVR calls depends on an external contact database of respondents' phone numbers, often obtained through a local project partner. The quality of a contact database can vary widely, and the following steps are recommended. First, ask the project partners to obtain consent from respondents to share the contact data within the project. The consent could be obtained by sending a text message by the local partner to all respondents, requesting them to send back a message if they agree to participate in the planned call campaign. Doing this step via partners would automatically clean out errors and out-of-date contacts and provide a consistent database with a pre-consent of respondents.

Next, pre-testing the question-tree integrity by running the IVR with the project team that developed the trees is recommended, for example, at the end of the tree design workshop. It is easier for them to identify mistaken linkages between tree branches than for the IVR operator. A wrong link can still be fixed before sending it to the target population. The test run is also the last opportunity for the team members to evaluate if the campaign complies with the 5Q principle: Keep it smart and simple.

Operating an IVR call should be straightforward when the above-listed recommendations are followed. However, before starting the call campaign, the lessons learned from all studies showed that respondents' awareness should be raised to achieve an acceptable call response rate (see Eitzinger et al. (2019) for evidence from Tanzania). Farmers who are informed by a project activity are more likely to respond to IVR. In most studies, the project implementers informed farmers through their project networks about the planned 5Q call campaigns. In the cases of extensive respondent lists, or when farmers cannot be informed through project activities, voice messages were sent introducing the research and explaining the purpose of the planned survey.

Furthermore, like a text message sent by a local partner for consent purposes, the voice message is another way of cleaning an extensive phone number database. For example, in Rwanda, the local project team started with 11'000 contact numbers. However, almost half of them did not connect to the voice message, and the first survey was started with a sample of 5'330 respondents. A text message was sent as a final reminder 30 min before every call to improve the response rate.

The configuration of the call campaign in the IVR system can also affect the response rate. In all studies, call campaigns were configured in similar settings. For example, a default call configuration setting was used to use a defined call time window between seven in the morning and eight at night. Also, the best time to operate the calls and have the highest possible response rate without interfering with the farmers' daily tasks was defined together with local project teams. Usually, between 2 pm and 7 pm was recommended as the best time to reach farmers in the afternoon. IVR was programmed to repeat calls with a call status failed in two intentions in quick successions of five min and repetitions up to two times, trying every hour (total six intentions); on detection of a voice mail, the call intention was stopped until the next programmed repetition.

Finally, cost estimation of programmed IVR call campaigns should be done and confirmed with the available budget. One of the main advantages of 5Q IVR surveys is low cost and time efficiency. Once an IVR system, either as its system or service subscription, is set up, call operations are often the lowest national costs for mobile phone airtime. In the studies presented in this paper, an IVR subscription service was used. A subscription service typically charges a monthly subscription fee (approximately between 500 and 1,500 USD) and operation costs for airtime. A rate of 0.04 USD per minute was paid in Rwanda, 0.05 USD per minute in Colombia and Ghana, 0.08 USD per minute in Uganda, and 0.1 USD per minute in Tanzania. The total cost of operating 1,000 calls of 5 min in all five countries, without including the costs for the IVR system, makes the sum of 1,600 USD: 200 USD for Rwanda, 250 USD for Colombia and Ghana, 400 USD for Uganda, and 500 USD for Tanzania. The call campaign could be operated in less than one hour.

DISCUSSION

Lessons learned from applying 5Q combined with IVR for agile data collection were presented. Call metadata from 44 call campaigns collected between 2015 and 2021 in Tanzania, Colombia, Uganda, Ghana, and Rwanda were analyzed.

Consistency of Phone Contacts Database

Farmers can change phone numbers rapidly or share sim cards within the household or even the community. In the first project piloting 5Q in Tanzania, farmer's phone numbers were registered as part of the pilot in resource-intensive door-to-door data collection. Unfortunately, many farmers changed from one service provider to another shortly after collecting the first IVR calls in 2015. A better way of collecting the phone numbers would be through inbound campaigns. At best, farmers would call into an offered service, e.g., a digital extension system or market price information system. After receiving the service, a 5Q feedback survey could be sent after time to the farmer. Farmers call into the system (or send an opt-in text message) and leave their phone number to get called back by the IVR system for operating the surveys.

For the following studies in Uganda, Colombia, Ghana, and Rwanda, farmer's phone contacts were obtained from project partners. When using contact data from external sources, it is more difficult to anticipate how many phone numbers might be outdated or collected a long time ago with a chance that it might have changed. In the findings of this study, there are some uncertainties in the analysis of call metadata about the comparison of failed calls among countries. In **Figure 3**, while calls in Uganda, Tanzania, and Ghana show a high rate of failed calls, Colombia only had 5% failed calls. In fact, in Colombia, the partner who provided the phone numbers sent a text message to all contacts in his database for the department of Cauca in the Southwest of Colombia (>400,000 text messages) and asked farmers to accept participating in the study by sending a text message with the text 'yes' back. In total, 1,240 farmers gave consent by responding positively to the text message. Also, in Rwanda, 10,998 phone numbers were received from the local project partners. As the first introduction and training call, a voice message was sent to all farmers. For the subsequent call campaigns in Rwanda, 5,330 phone numbers were used from contacts who successfully participated in the introduction and training call, partly explaining the lower rate of failed calls, 22% in Rwanda. Comparing a series of four calls between the years 2019 and 2021 in Rwanda (**Figure 6**) confirms that most failed call intents remained the same all four calls, which further indicates that these contacts were not updated or the sim cards were not used anymore.

Finally, another option would be using a random digit dial (RDD) sampling strategy and start the survey with an eligibility question. The response rate in random digit dial surveys may be lower but could achieve representative sampling at a low cost. A recent study that carried out RDD surveys in nine LMICs shows that the average response rate for RDD IVR surveys vary between 7 and 60% (39% in Rwanda, 11% in Uganda, and 25% in Colombia) and found that the most significant limitation on response rates is to reach the start of the survey, even if they have responded to the call (Dillon et al., 2021). Other studies calculated a standardized response rates from the number of completed interviews, partial interviews, refusal or break-off, non contact and others to validate RDD surveys against other survey research methodologies (L'Engle et al., 2018).

How to Improve the Response Rate of IVR Call Campaigns?

Evidence from RDD surveys shows that strategies to increase response rates should focus on increased pick-up rates and improved first impressions of respondents (Dillon et al., 2021). In the context of agricultural development projects, increased pick-up rates and effective start of the survey can be achieved by several measures. First, a bigger pool of phone numbers increases the chance to reach the desired response rate. Second, using the project's communication channels to announce IVR call campaigns increases response rate, e.g., announcing them during a focal-group workshop, through the voice of community leaders, or sending text messages to respondents ahead of the first call campaign. Next, if the phone numbers were received from partners, ensure the partner runs a quality control to remove outdated contacts before handing over the database. Finally, to avoid a respondent hanging up shortly after starting the call, the introduction is vital for staying in the call. The introduction should reveal who or what institution is calling, explain the purpose of the call, and benefit from the collected data. For research and academia, ethical standards for research that involves human subjects are often institutional policy and provide clear guidelines for the consent of a respondent of phone calls in research activities.

If the study requires several call campaigns, it is also essential to consider that respondents might not pick up in a subsequent call or change their consent between calls from yes to no. **Figure 6** shows the change of the same respondents' responses to the first consent block in each call. Finally, the type and topic of the call are relevant for the response rate and completion status. Results show that calls with only one block to introduce the research to a farmer or explain how the IVR call works (training call) had a much higher completion rate than other call types that involve a set of question blocks. The finding supports the basic idea of 5Q to keep call campaigns short.

Furthermore, it suggests setting up call campaigns in small packages that can be run as connected blocks on an IVR system and allowing a resumption of the call campaign on uncompleted blocks. Besides the length of a call, the research topic was also relevant for a higher response rate. Although some topics like covid-19 can attract more attention by respondents, and the imposed travel restrictions for agricultural fieldwork can also increase call campaigns response rate during the time of imposed restrictions, the higher response rate was also found on research topics about services that farmers receive. For example, the response rate of call campaigns evaluating climate services for farmers in Rwanda (CS in **Figure 5**) showed similarly high levels as the call campaigns on impact from covid-19 (COVID in **Figure 5**). The same response rate can also be observed at call campaigns collecting feedback after a training workshop in Tanzania (CM in **Figure 5**). Finally, the response rate also depends on cultural and regional differences.

Keep It Simple

Unlike other data collection methods and tools, 5Q moves from simply collecting data to using data from multiple sources to give a clearer idea of KAS. Following the 5Q key message of keeping it simple and asking five smart questions suggests using the KAS approach as a framework for developing question trees. Since knowledge is the first step for many farmers to adopt a new agricultural innovation (outcome propositions), attitudes toward new practices depend on a combination of the individual's belief that it will lead to the desired outcome (outcome beliefs) and the values they attribute to those outcomes. KAS identifies people's perceptions of a new practice, technology, or service. Understanding cognitive barriers and drivers for adoption is essential for knowledge transfer strategies in agricultural development projects. Skill for subsumption knowledge transfer into farmer practice is the last and main desirable change (outcome skills). It generally occurs because of previous knowledge, skills, and attitude toward a practice or service. Thus, following KAS for developing question trees is the simplest way of applying 5Q to a project, but is not the only one, and the best strategy for developing a project questions tree should be developed in participatory sessions between project implementers and an experienced researcher of developing a 5Q strategy for an agricultural development project.

How to Use IVR and 5Q Successfully in Research?

In this study, call metadata was analyzed to demonstrate how the 5Q concept combined with IVR systems can achieve cost-efficient and agile data collection. Though results show some evidence of response and saturation rates in different call campaign types, the study did not validate sample interactions to understand better why some respondents carried on to the end of the blocks while others dropped the call earlier. Also, differences of respondents in terms of social inclusion, literacy, and digital literacy have not been considered for the analysis, which might represent a gap in the presented findings drawn from call metadata and experiences from implementers of 5Q call campaigns only. Therefore, future research should identify respondents' saturation rates and reasons for early dropout during IVR call campaigns. Further, issues of unintended social exclusion should be studied to understand better what external factors, like lack of access, resources, or knowledge, lead to exclusion and identify the best-bet digital communication channels to reach them using the 5Q approach for feedback collection. Finally, other barriers like the social norm, lack of self-efficacy, and lack of perceived usefulness, can lead to low response rate or quick saturation of call respondents in 5Q call campaigns and need to be further studied.

CONCLUSION

The study demonstrates how 5Q can be combined with cost-effective IVR call campaigns and help agricultural development projects incorporate feedback mechanisms, such as building evidence of what works and what does not in terms of adoption. 5Q is a concept that uses the principle of keeping data collection smart and simple by asking five thoughtful questions in question-logic-trees in repeated cycles or rounds and using cost-effective digital communication tools for data collection. 5Q moves from simply collecting data to building evidence of farmers knowledge (perception), attitudes, and skills for adopting a practice.

5Q follows a process that starts by identifying questions that are linked to a project's theory of change. Next, a logic question-tree structure and question blocks are used to create a automatable sequence that can be used to program a IVR system. This study analyzed call metadata from 44 IVR call campaigns in five countries. Three different call statuses were analyzed as percentage of complete, incomplete, and failed calls, to understand differences between countries, call type, and campaign topic.

Overall, results show that response rate and call completion for IVR calls vary between countries, call types, and survey topics. Response rates, including complete and incomplete surveys, were highest in Colombia with 95%, followed by Rwanda with 78%. However, in Rwanda, the rate of call completion was higher than in other countries, with 38%. The study also found that higher response rates can be achieved by increasing the pick-up rate and improve the first impressions of respondents about the call campaign topic.

Future research should focus on better understanding what leads to a respondents' saturation and early call dropout during IVR call campaigns. Further, issues of social exclusion that can happen unintentionally, should be studied to understand better what external factors, like lack of access, resources, or knowledge, lead to exclusion. Finally, by identifying wich digital channel works best in a region and for a social group, possible social exclusion could be avoided.

DATA AVAILABILITY STATEMENT

The call metadata used for the analysis are available on: https://doi.org/10.7910/DVN/CMIVQK.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Institutional Review Board of the Alliance of Bioversity International and CIAT. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

AE supported the implementation of research in all studies countries, analyzed all metadata, and wrote the manuscript.

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Where Is My Crop? Data-Driven Initiatives to Support Integrated Multi-Stakeholder Agricultural Decisions

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Globally, there has been an explosion of data generation in agriculture. With such a deluge of data available, it has become essential to create solutions that organize, analyze, and visualize it to gain actionable insights, which can guide farmers, scientists, or policy makers to take better decisions that lead to transformative actions for agriculture. There is a plethora of digital innovations in agriculture that implement big data techniques to harness solutions from large amounts of data, however, there is also a significant gap in access to these innovations among stakeholders of the value chains, with smallholder's farmers facing higher risks. Open data platforms have emerged as an important source of information for this group of producers but are still far from reaching their full potential. While the growing number of such initiatives has improved the availability and reach of data, it has also made the collection and processing of this information more difficult, widening the gap between those who can process and interpret this information and those who cannot. The *Crop Observatories* are presented in this article as an initiative that aims to harmonize large amounts of crop-specific data from various open access sources to build relevant indicators for decision making. *Observatories* are being developed for rice, cassava, beans, plantain and banana, and tropical forages, containing information on production, prices, policies, breeding, agronomy, and socioeconomic variables of interest. The *Observatories* are expected to become a lighthouse that attracts multi-stakeholders to avoid "not see the forest for the trees" and to advance research and strengthen crop economic systems. The process of developing the *Observatories*, as well as the methods for data collection, analysis, and display, is described. The main results obtained by the recently launched Rice Observatory (www.riceobservatory.org), and the about to be launched Cassava Observatory are presented, contextualizing their potential use and importance for multi-stakeholders of both crops. The article concludes with a list of lessons learned and next steps for the *Observatories*, which are also expected to guide the development of similar initiatives. *Observatories*, beyond presenting themselves as an alternative for improving data-driven decision making, can become platforms for collaboration on data issues and digital innovations within each sector.

Keywords: agricultural indicators, open-access datasets, cassava, rice, *Crop Observatories*

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INTRODUCTION

Currently, many consider data what oil was for the industrial revolution (Economist, 2017), a valuable resource and organizational asset (Lake and Crowther, 2013; Birch et al., 2021). For many companies (e.g., Amazon, Facebook, Google, Microsoft, Tesla), data are their most valuable commodity, an asset that has generated billions of dollars for the world economy. The current disruption around data and digital innovations has led to what some have called the fourth industrial revolution (Schwab, 2017). Technologies such as a blockchain, the Internet of Things, artificial intelligence, and immersive reality are rapidly changing the dynamics of various economic sectors. The agricultural sector and food sector are not an exception to this revolution; nonetheless, their transformation process compared with that of other sectors has a long journey ahead as agriculture trails most sectors in digitalization (Manyika et al., 2015). Although some countries have quickly moved toward digital transformation thanks to the spread of information technologies (IT), most developing countries still have several barriers to overcome before tapping into the potential benefits of this revolution. There is a general warning to avoid the rise of a digital divide[1] as it could leave behind the most vulnerable actors of the agricultural sector (i.e., smallholders), who may not be prepared to easily adopt new technologies (Trendov et al., 2019; Zhai et al., 2020). Most developing countries still have weak technological infrastructure, low levels of e-literacy, and restricted access to and high costs of digital services that can limit the digital revolution benefits in agriculture (Trendov et al., 2019). Nevertheless, diverse international development agencies and multiple research initiatives are working to open data access and ensure that all actors in this critical sector benefit in the long term from this new revolution.

Open data provide a unique opportunity to strengthen agriculture, with benefits such as encouraging collaboration between institutions to answer global research questions of relevance. Besides supporting researchers and policymakers, open-access data provide a unique opportunity to improve agricultural management decisions and influence the entire food supply chain. For example, farmers can improve their decision-making processes by receiving site-specific recommendations about sowing times, best-available varieties, and adequate input use and timing. They can also receive recommendations from early warnings of pests and diseases and obtain access to financial services, among other management-related decisions or services (Wolfert et al., 2017; FAO, 2021c). Meanwhile, consumers could benefit from information on how to find farmers' markets, crop nutritional information, and the use of blockchain technology to ensure food safety, among other benefits (Allemang and Bobbin, 2016). These are just a few of the multiple benefits that exist to encourage the digitalization of agriculture, which can reach other stakeholders within the food systems and further expand their impact. However, this requires thinking outside the box and carefully considering its implementation to avoid leaving the most vulnerable out of reaping potential benefits.

Although several ongoing initiatives are making significant efforts to advance digital agriculture, data use in agriculture has a long history, even before the digital revolution began. The Food and Agriculture Organization of the United Nations (FAO) created FAOSTAT (formerly known as AGROSTAT) in 1986, which up to now is the most comprehensive repository of national agricultural statistics for 245 countries with more than 12 domains that go from production to trade, prices, food security, emissions, investments, forestry, and other topics (FAO, 2021a). Other international institutions such as the World Bank have been compiling macro indicators that track development progress nationally, several of which are related to the agricultural sector (World Bank, 2021). In addition, multiple national or regional initiatives collect and present relevant agricultural data. Antognoli et al. (2017), Piestrak (2020), and Michigan State University (2021) have compiled comprehensive inventories of open information repositories in agriculture.

Nonetheless, data is only one part of the equation. Analyzing and disseminating data-driven recommendations are essential to strengthen the agricultural sector, and with such amount of data, it is important to implement technologies that make the most of the available information. Big data tools have been at the forefront of the digital revolution, with a handful of initiatives developed in agriculture. However, access to these tools and other technologies is disparate, leaving the most vulnerable behind. Global platforms such as the CGIAR Big Data Platform (CGIAR, 2021a), G.E.M.S.® (UMN, 2021), and GODAN (GODAN, 2021), have been unraveling Big Data's potential to solve agricultural development problems, while advocating for more equitable access and openness of data. Nonetheless, these and other efforts are far from reaching their potential. While access to this information is improving, the gap between those who can take advantage of the available data and those who cannot is persistent.

Under this new revolution and sea of data and platforms, and stakeholders with very diverse capabilities and needs, how can efforts be integrated to make the most of the data available and leave no one behind? This article introduces the *Crop Observatories*, not as a unique answer to the question posed, but as one of the many alternatives needed to solve it. These *Observatories* were born from the need to have relevant indicators for specific crops (e.g., rice, cassava, common beans, banana and plantain, and tropical forages), providing data-driven insights to scientists, policymakers, farmers, and consumers. The *Observatories* merge diverse datasets that help to contextualize the importance of the crop of interest within the agricultural sector from diverse points of view, with the main objective of generating data-driven decisions.

To achieve this, the *Observatories* do not only rely on international open-access datasets, as they have also made a significant effort to compile nationally relevant data sources (e.g., data from national censuses and government or research institutions). Apart from the commonly used country-level indicators, these nationally relevant data sources provide granular levels of information. Likewise, the *Observatories*

[1]Digital divide is the term used to refer to the risk of having potential benefits unequally distributed between sectors and actors of the agricultural sector (e.g., rural vs. urban areas, gender inequality, youth population) (Trendov et al., 2019).

are merging farmer household surveys, integrating and improving dataset ontologies and providing relevant crop-specific indicators. Furthermore, they are built upon large networks of public-private partners, who constitute not only a source of information but also a broad network of users who engage with the data, thus helping to reach a wider audience. Finally, the *Observatories* are integrating the scientific evidence of available innovations for each crop, by linking information from gene bank accessions and adoption of improved varieties from breeding programs to farmers' fields.

The article presents an overview of open-access data initiatives in agriculture, highlighting the use of big data to leverage this information and the limitations it presents for smallholders. The *Observatories* are then introduced, presenting its data management and the structure, and subsequently providing examples of its potential use in decision making, as well as the corresponding development of collaborative multi-stakeholder networks that has been achieved within the initiative. The article concludes by listing lessons learned that are contrasted with findings of other authors, and next steps to contribute to the development and improvement of the *Observatories* and similar initiatives in agriculture.

LITERATURE REVIEW

Global Open-Data Inventory for Agriculture

Open-access data have a long tradition in agriculture, starting with the legacy of AGROSTAT, the first agricultural information platform developed by FAO in 1986, and renamed in the mid-1990s as what is known today as FAOSTAT. This initiative has moved through a series of programming languages and operating systems, and has grown in data quantity, coverage, and type of information collected (Mori, 2018). FAOSTAT is now the most comprehensive repository of national agricultural statistics and undoubtedly the main, and in many cases the only, source of open information nationally for a wide range of agricultural indicators.

Beyond FAOSTAT are a plethora of initiatives aimed at collecting and providing access to open datasets related to the field of agriculture. Antognoli et al. (2017) make a comprehensive inventory of public online databases and repositories containing agricultural data up to 2017, in which datasets of journals, ontologies, and other ag-specific open-data resources are found. Also, catalogs such as those of Piestrak (2020) and Michigan State University (2021) present more limited but more up-to-date inventories[2].

International organizations (e.g., CGIAR, OECD, United Nations, World Bank) that compile national statistical information from many countries are the main leaders of initiatives that provide general indicators, trade, or agricultural *databases*. National statistical agencies are their main sources of information, and they often contain more detailed information than that presented in the global or regional databases. However, the information is dispersed, and its management hinders accessibility, interoperability, and comparability of data between different sources of information at disaggregated levels. In some cases, depending on the leading institutions presenting the information, there may be sources presenting different values for the same variable. There is still a need to improve metadata reporting among data providers and collectors to have consistent statistical information that can be replicable and interoperable for making better decisions.

In the categorized *databases* (**Supplementary Table S1**), two particularly excel in presenting genomic information that standardizes different crop species for comparative purposes (McCarthy et al., 2007; Tello-Ruiz et al., 2021), corresponding to more specific information with a smaller audience than the other *databases*. Similar resources also exist for a wide range of crop groups and species. Examples include the open-data genetic resources available for legumes in the Pulse Crop Database (Humann et al., 2019), or RIKEN, which has established a genomic platform for cassava (Utsumi et al., 2012). Correspondingly, the Rice Annotation Project database has been providing a comprehensive set of gene annotations for the rice genome sequence that can be freely accessed (Sakai et al., 2013). Furthermore, Thudi et al. (2021) review similar resources for 12 kinds of cereals and legumes.

Other databases such as AgIncentives, the Agri-food Data Portal, and the Policy Support and Governance Gateway, concentrate on policy-oriented information to guide policy implementation (IFPRI, 2019; European Commission, 2021). The International Food Policy Research Institute (IFPRI) has also developed the COVID-19 Policy Response Portal, a tool for monitoring policy responses to COVID-19 in 33 countries and nine policy response areas, tracking to date more than 2,800 policies implemented worldwide since the onset of the pandemic (IFPRI, 2021).

Regarding price information, FAO (2017) presents a review on price systems globally and Magesa et al. (2014) analyze these price systems in developing countries. Futures and cash prices of the main commodities in the stock exchange markets are additional market information freely available. Although each market has its real-time information system, initiatives such as Streak,[3] Trade Station,[4] and TradingView,[5] offer free information for commodities traded on the main markets. These platforms also offer a set of tools for creating, analyzing, and testing trading strategies, some of which are open source and interoperable with other platforms.

The functionalities offered by most platforms to access them are as diverse as the types of databases: from simple visualization and downloading of the data presented on most platforms (**Supplementary Table S1**), to powerful search engines and functionalities that allow greater user interaction with the data. Such are the examples of the United States Department of Agriculture (USDA) Economic Research Services Data Visualization Platform (USDA, 2021), and FAO's comparison

[2]In the supplemental section (**Supplementary Table S1**), we present a list of selected open-data sources, repositories, and platforms for agriculture, which we categorized using the main types of initiatives (i.e., databases, repositories, and platforms) and the leading institutions (**Supplementary Figure S1**).

[3]The corresponding link to the site is https://www.streak.tech/.
[4]The corresponding link to the site is https://www.tradestation.com/.
[5]The corresponding link to the site is https://www.tradingview.com/.

tool for food prices (FAO, 2021d) and FAOSTAT indicators (FAO, 2021b).

Other tools allow more dynamic interaction by visualizing data using maps. An example is the FAO Water Productivity Open-access portal (WaPOR), a publicly accessible near real-time database using satellite data that allows the monitoring of water productivity in agriculture in some African countries (FAO, 2020b). Other initiatives combine different types of data as input for the generation of more complex analysis systems. For example, the Global Information and Early Warning System (GIEWS) developed by FAO integrates price data with cartographic information from crop monitoring and agricultural inventories to provide early warnings on food supply, demand, and price problems (FAO, 2020a). Another initiative that integrates data from multiple sources is the Hand-in-Hand geospatial platform, a support tool for geospatial modeling and analysis to identify opportunities for and vulnerabilities of rural populations by integrating data and human capital from more than 20 multi-domain technical units across FAO (2021e).

Moreover, the USDA, FAO, and the CGIAR have made significant efforts to create agriculture-related *dataset repositories* on a wide range of topics. One of the oldest initiatives is AGRIS, which officially started in 1974, but decades later was brought into a more advanced repository with millions of bibliographic records (publications and datasets in diverse languages) available online. It is also in this group that we identified specialized repositories with more specific topics such as genomics and geospatial information of relevance for agriculture, and more general repository initiatives such as the Harvard Dataverse repository, which compiles thousands of datasets that go beyond agriculture and supports data management for its users (King, 2007; Yang et al., 2021).

Finally, several global platforms aim to unravel big data's potential to solve agricultural development problems; some selected examples presented in **Supplementary Table S1** are the CGIAR Big Data Platform; G.E.M.S®, an international agro-informatics alliance; and the Global Open Data for Agriculture and Nutrition, a network with more than 1,000 innovators around the globe, all of them with the objective of providing research tools for better decision-making and strengthening of the agricultural sector. However, the inventory presented here and in **Supplementary Table S1** is just a glimpse of all the initiatives that seek to tap the potential benefits of open data and digital agriculture, as there are many more, ranging from small initiatives generating microdata at the farm level, to large ventures collecting large amounts of data.

Big Data and Smallholders

While the growing number of open data initiatives has improved the availability and reach of data, it has also made it more difficult to analyze this information, widening the gap between those who can process and interpret this information and those who cannot. Big data has emerged as a potent digital tool for harnessing the potential of open data in agriculture. However, despite the huge expectations around the benefits that big data innovations or analysis could provide to farmers (WEF, 2012; Porciello et al., 2021), concerns remains as to whether these benefits could be equally acquired or at least reached to most farmers and other stakeholders in the value chains. Fully attaining these benefits is further exacerbated by a large digital divide between big and small holders, with the latter facing major constraints to fully grasp these expected benefits (Protopop and Shanoyan, 2016; van Etten et al., 2017).

Factors contributing to this gap are as diverse as the contexts in which big data innovations are implemented. Some of the most common constraints faced by smallholders relative to other producers (e.g., medium and large holders) are weak digital infrastructure, affordability, and low levels of e-literacy, and digital skills (Wolfert et al., 2017; Trendov et al., 2019; Porciello et al., 2021). This lack of basic conditions to embark into the digital transformation accentuate differences between producers, but also among countries, since many developing countries still struggle with underlying economic problems that further exacerbate the aforementioned constrains, limiting the expected benefits that the digital revolution can have on agriculture (Trendov et al., 2019). Even at the household level, there is evidence of significant gender gaps in access to these solutions and their benefits (Porciello et al., 2021).

These disparities in access to innovations and the expected benefits from their adoption will accentuate the already existing gap in productivity, access to market information, or other competitiveness factors whose unequal access may translate into greater social and economic disparities between groups of producers (Trendov et al., 2019). As big-data solutions become more relevant in agriculture, major shifts are expected in the roles and power relations between different actors in food chains (Wolfert et al., 2017), and developers and researchers should be responsible to avoid leaving some of the vulnerable actors behind. Significant barriers to entry may arise for the most vulnerable groups, as there is an increased concentration of technology in a limited group of producers, limiting the role of smallholder farmers in the digital transformation process (Trendov et al., 2019). On the other hand, the limited capacity of smallholders to deal with the complexity of data, coupled with their double role as producers and potential users of big data, prevents the institutionalization of this innovations at the producer level, leaving room for other actors in value chains to control this information (Lioutas et al., 2019).

Besides the risk and unfavorable conditions faced by smallholders, they are responsible for cultivating around 40% of global agricultural land and represent nearly 570 million famers (Burra, 2019), so ensuring that they benefit from the digital revolution is of paramount importance. Cost of inaction to support smallholders could further increase inequalities (Sylvester, 2019). This adds to the imminent risk of smallholders losing confidence in big data solutions. An extensive review of impact studies of digital innovations for middle and low-income countries compiled 312 studies of which 288 (92% of all studies) evaluated innovations targeting smallholders, and for 126 of those studies the authors found significant positive results for income, yield, knowledge, or resilience, among other outcomes (Porciello et al., 2021). This wealth of evidence has fueled national and global coalitions that aim to help developing countries collect and analyze data on smallholder farmers as a strategy to achieve the Sustainable Development Goals by providing them with big data solutions (Tollefson, 2018; Sylvester, 2019).

Porciello et al. (2021) review shows that the main modality for disseminating digital innovations is cellphones, mainly using text-messages, phone calls, or smartphone apps to provide guidance to farmers (in 62% of the studies). Other relevant digital modalities used are videos (23%) and websites (12%). This shows that most digital innovations attempt to benefit from the latest expansion of mobile communications in rural areas to reach the majority of farmers (Trendov et al., 2019). It is also noted that most of the innovations evaluated are in Sub-Saharan Africa (specifically Kenya, Nigeria, Uganda, Ghana, Tanzania, and Ethiopia), accounting for almost half of all studies analyzed, and India, with a surprising 27%. Clearly, it is necessary to continue to expand the scope of digital solutions to other regions of importance, such as the rest of Asian countries, given that the region concentrates the largest number of poor people worldwide (World Bank, 2021), or Latin America which has a complex biodiverse system that can still improve its productivity and become a net food exporter (Andrade et al., 2021).

In addition to this current concentration in the modality and geographical distribution of the innovations listed, there is a heterogenous set of value chains where these innovation have been implemented, with cereals (19%) and livestock (8%) having the largest shares. Finally, there is an extensive list of multiple factors that facilitate the adoption and scaling of innovations (Porciello et al., 2021), which helps to have a broader idea of those key factors to take into account in relation to the use of digital technologies with smallholders, but also warns about the heterogenous context that is required in each specific condition when disseminating these innovations. Despite the direct benefits for smallholder farmers, big data solutions generate positive spillover effects that link farmers to other stakeholders in the value chains, such as the financial sector through credit access production insurances, or digital banking that facilitates transactions and strengthens production. Other actors that can benefit of these spillovers are service, logistics and transport providers (Narayan et al., 2019), as well as consumers themselves (Allemang and Bobbin, 2016; Porciello et al., 2021). In some cases, these solutions, through their benefits, can come to act as factors that articulate stakeholders within a value chain, but long-term investments and multi-stakeholder coordination is needed (Wolfert et al., 2017).

Big data solutions represent an important alternative to leverage the use of open data and benefit smallholders and other stakeholders of the value chains by generating knowledge that contributes to timely decision making (Protopop and Shanoyan, 2016). While the potential of these tools for improving the lives of smallholder farmers and other stakeholders is enormous, it is important to address several concerns around these initiatives. Big data limitations include data availability, representativeness, and quality. Boyd and Crawford (2012) present a critical view on this topic, arguing that despite the radical change big data is creating in how we think about research, we should consider that data is useless when it separates from researchers' interpretations, methodology, and context. Further, aspects related to data ownership and control, data security, privacy, and ethical issues are a primary concern for stakeholders and evidence of the need for adequate policies to leverage big data tools (Kamilaris et al., 2017; Rotz et al., 2019). It is also necessary to develop appropriate incentives to create bi-directional data-output sharing relationships between farmers, especially smallholders, and private ventures (WEF, 2012; Zhang et al., 2021), thus providing value-added alternatives to producers. Generating relationships of trust between and in the big data solutions and agricultural actors as such. Moreover, access to these solutions and the interpretation of their results remain a major constraint to overcome.

One solution does not fit all, as there are a multitude of alternatives that are already addressing some of the above-mentioned issues. In this article, *Crop Observatories* are presented as one of these alternatives, with the aim to guide the decision-making process around specific crops and the needs of different types of stakeholders in these value chains. They also aim to address the issue of access to reliable data, which remains a constraint for many smallholder farmers. Moreover, while many digital solutions have proven to be successful and have a positive impact on smallholder farmers in developing countries, there is an over-concentration of these solutions in a handful of selected countries (Porciello et al., 2021), whereas *Observatories* have a broader scope by not only having a global reach, but also by presenting the importance of contextualizing a user's reality in relation to the rest of the world. In addition, *Observatories* respond to the need to synthesize information by integrating data sources and making it not only more accessible, but also more understandable to a wider audience. While the potential of platforms among impactful digital solutions remains limited, as does the reach of big data products and their benefits to small producers, there is great growth in digital coverage and services in the developing world (Trendov et al., 2019), representing a great potential to drive these innovations and ensure that the most vulnerable are not left behind in this revolution.

MATERIALS AND METHODS

Crop Observatories Structure and Data

These Observatories were established from a demand-driven request to provide relevant indicators for specific crops, with the initial intention to guide scientists and disseminate the scientific knowledge gathered by the Alliance Bioversity-CIAT. Nonetheless, their scope grew continuously by adding new modules and components of interest to other stakeholders (e.g., policymakers, smallholder and large farmers, intermediaries, industry, and consumers) that demand and benefit from more specific and data-driven information. The main objectives of the *Observatories* are to (i) merge and manage diverse open-access datasets that disaggregate relevant indicators to lower administrative units, and contextualize the economic importance of the crop regionally and nationally; (ii) combine and display specific datasets from multiple research areas (i.e., gene banks, breeding programs, socioeconomic units, food quality and sensory laboratories) under standardized ontologies for analysis; and (iii) link and share this information with an extensive network of partners related to the crops of interest for the

Alliance Bioversity-CIAT (e.g., rice, cassava, common beans, banana and plantain, and tropical forages). Each observatory concentrates only on a particular crop or group of crops to provide a complete overview of its relevance regionally and nationally from multiple points of view.

Many crop scientists rely on open-access datasets to contextualize their crop's importance nationally or regionally. For decades, FAOSTAT has provided relevant official agricultural indicators to fulfill these needs. Although this source of information is useful, and in most cases the only source of information, the level of aggregation and availability of crop-specific variables is often limited. Our *Observatories* therefore attempt to overcome this limitation by continuously harvesting from various open-access datasets, which, although not exhaustive, complement more disaggregated sub-national information to better understand the context of the crop in each country and thus guide more tailored intervention decisions that could diminish the digital divide and benefit large and smallholder farmers. In the supplementary material, we detail an inventory of datasets that feed the rice and cassava *Observatories* (**Supplementary Table S2**), and for each we have estimated a quantitative FAIR measure[6] that evidences a lack of FAIRness among certain agricultural databases (**Supplementary Figure S2**), which could limit their access and usage. Datasets coming from international datasets present higher scores than most national dataset initiatives, showing an opportunity to strengthen their management. It is worth noting the great variability among information sources, as some are limited to statistical tables or reports without metadata that do not even come close to being considered open-data information platforms such as those international databases described earlier in this section.

Although access to disaggregated agricultural data indicators is a first step, to answer more specific or complex research questions, there is a need to strengthen the interoperability between datasets that come from diverse research areas and have heterogeneous objectives. The observatories emulate the proposed approach by generating interoperable datasets that connect data from different units and sources, with the objective of providing a comprehensive view for research, development and scaling of technologies. For example, by connecting data from gene banks, breeding programs, extension units, and socioeconomic datasets, a complete overview of research, development, and scaling-up of innovations, such as improved varieties, can be created. This will aid in tailoring specific breeding targets that generate the greatest possible impact, contributing to increasing producers' and consumers' welfare while coping with the uncertainty of climate change. Some of the main sources of this information are institutional records, expert opinions, and more detailed household surveys that require standardization procedures to maintain consistent ontologies that allow us to generate insightful lessons. Building datasets of this nature usually requires major logistical efforts and expenditures, and often is not fully exploited unless the datasets are findable, accessible, interoperable, and reusable (FAIR) enough to generate insightful analysis.

Besides dataset disaggregation and interoperation, the final piece of the *Observatories* is to generate and display data-driven analysis that becomes valuable for diverse users. Users play an important role in guiding a demand-driven observatory, while helping to disseminate observatory information and outcomes throughout their networks. We build each observatory upon a network of relevant actors in the crop value chain. This network is composed of stakeholder from international organizations, farmers associations and public and private institutions interested in developing lessons from the information they compile and incorporate into the observatory. Currently, the *Rice Observatory* network mainly relies on the institutions belonging to the Latin American Fund for Irrigated Rice (FLAR, its acronym in Spanish), while the *Cassava Lighthouse* mainly relies on the Cassava Breeding Program of the Alliance Bioversity-CIAT, which has an extended network of industrial cassava processors, research and government institutions from Southeast Asia and Latin America. Another example is the *Common Bean Observatory*, currently under construction, which will rely on the Pan-African Bean Research Alliance (PABRA), one of the largest research networks in sub-Saharan Africa for common beans.

The first observatory launched was the *Rice Observatory* (www.riceobservatory.org), which attracted attention from other research areas that decided to establish their own web-based open-access platforms. The *Cassava Lighthouse* (www.cassavalighthouse.org) is expected to be functional by the end of December 2021, while the *Common Bean*, *Musa* (banana and plantain), and *Tropical Forages Observatories* are in the initial stages of establishment and are expected to be released by mid-2022.

Crop Observatories Data Management and Methods

The *Observatories* follow a non-rigid standard set-up procedure that allows us enough flexibility to adapt them according to users' needs. *The Observatories* begin with a general contextualization process led by multidisciplinary researchers from breeding, agronomic management, and socioeconomic programs in the Alliance Bioversity-CIAT, who identify relevant data sources, prioritize topics of interest, and define a target audience and network of partners for the appropriate observatory. Consequently, each observatory has unique characteristics associated with the particularities of each crop, the profiles of the end-users, and the needs of the sector. Nonetheless, a baseline structure with standard indicators and similar data visualization facilitates cross-analysis when necessary as well as knowledge sharing and collaboration between researchers and developers of the initiatives.

Once each observatory is conceptualized and relevant data sources are identified, the next stage is to select and compile data from these sources of information (see the example in

[6]FAIR measures are defined from the principles of Findable, Accessible, Interoperable, and Reusable (Wilkinson et al., 2016, 2018). The specific measurement procedure is described in detail in GARDIAN Fair metrics available at CGIAR (2021b).

Supplementary Table S2). Although the data sources used are usually referred to as official sources of information, they undergo a rigorous review, cleaning, and analysis process before being published in *an observatory,* a process that is sometimes complemented with the help of strategic partners in order to identify the most relevant sources of information according to the topic or country of interest. Their structure, accessibility, interoperability, and replicability vary and represent a critical factor to consider when selecting the sources of information.

The observatories are complemented by information from their network of partners. A specific example of this complementarity in data collection is the yearly Monitoring and Follow-up Survey for the Latin American Rice Sector (EMSAL, its acronym in Spanish), distributed among members of FLAR since 2014 to collect sectorial information. Although the response rate and continuity in answering the survey vary among members, the tool is constantly revised, and the *observatories* continue to seek strategies to improve the quantity and quality of the information collected through key informants of the network. Furthermore, the institutions belonging to the observatories' networks follow a specific Data Management Policy (see **Supplementary Material S3** for a complete version) based on international property rights principles and the CGIAR Open Access and Data Management Policy (CGIAR, 2013), ensuring confidentiality of the provided data when necessary and establishing the precepts for the proper handling and safeguarding of shared data.

The next steps are related to data management, processing, cleaning, standardization on variable units, and structure of the datasets. The most comprehensive sources of information, such as FAOSTAT, have an Application Programming Interface (API) service, which facilitates data downloading and updating processes. Currently, observatories are developing an automated service in R software that makes it possible to extract data from the FAOSTAT API, relate the information to local databases, select the data for the crops of interest and calculate the indicators to be displayed in the observatory. This is a process that stems from the lessons learned in the development of this article and that we hope to scale to other sources of information (e.g., price and market information databases), with the objective of not only maximizing efficiency in data downloading and updating, but also in the standardization of processes and the implementation of novel analytical techniques for large volumes of data.

Datasets have a tall-narrow system, with standardized single units of measurement. In general, national-level databases have nine mandatory variables (e.g., region, country, ISO-country, element, year, value, unit, sources, and observations). The sub-national-level databases include additional mandatory variables to identify sub-national administrative levels within a country (e.g., state, province, department, municipality). Geospatial identification is of importance in each dataset for data visualization. Data management is facilitated by storing datasets by topic of interest within each observatory.

Then, the observatories generate and display specific interactive graphical charts and figures for data visualization, intended to provide a better understanding of the crop and its context for a more accurate decision-making process, encouraging the identification of relevant research questions for scientists in a simple way. The Alliance's Foresight and Applied Economics for Impact unit carries out these processes throughout its observatory focal points, through which each researcher meets with the team of developers from the Data Management and Research Methods unit to share the databases and any other information relevant for presenting their data visualization ideas.

After receiving the data with the analysis results, the development teams use a workflow that standardizes the data into a single format that will conform to the structure of each platform. The developer translates the variables for each dataset into JavaScript objects. An object-relational mapper (ORM) converts the objects into the corresponding relational database structure and generates database extraction, translation, and loading (ETL) scripts in the Structured Query Language (SQL) to add the new data. Finally, the developer uses the ETL scripts to add the new data into the database. When an observatory user wants to visualize the data on the client side (web or mobile browser), GET method[7] requests of Hyper-Text Transfer Protocol (HTTP) are made with native JavaScript to retrieve the data. On the server side, the platform's business logic, contained in program constructs referred to as "controllers," loads data from the database and transfers the data to the client using JavaScript Object Notation (JSON). The client then executes functions that visualize the data in the desired way.

We construct the *Observatories*' websites using open-source technology. We use MySQL as the database engine and we develop the web applications using the Laravel web application framework, a free and open-source PHP (general-purpose script language) framework. The look and feel of the platform use Bootstrap, a free and open-source CSS (Cascading Style Sheets) framework. We also use open-source libraries such as mapbox.js (Gundersen, 2017), Chart.js (Downie et al., 2021), Plotly.js (Johnson et al., 2021), and TradingView widget (Ivanov et al., 2021) for data visualization of maps or charts tailored to end-user needs. Furthermore, the *Observatories* implement Programmable Google Search Engines to filter the most relevant and up-to-date news, categorized among various topics of interest.

Finally, the development team performs various tests to verify that everything is working correctly. Every new functionality is initially uploaded to the test server for verification by a multidisciplinary team of researchers. Once changes are approved, they become part of the production server, in both the database server and the web application server containing the observatory. It is essential to emphasize that this whole process is cyclical. Researchers and developers verify and update the visualized data to ensure the best end-user experience. This complete effort depends upon a multidisciplinary team that includes economists, software and data engineers, agronomists, food scientists, plant breeders, and communication experts.

[7]This method allows consulting information between the server and client to retrieve the information requested.

RESULTS

The *Observatories* are structured to contain the topics prioritized by all relevant actors, and they continue to evolve as new sections are incorporated. The *Observatories* offer data visualization products categorized into different topics of interest. These tools integrate data from different sources with further analysis to provide insightful views of the crop context nationally, and thus orient decision-making processes and research among all types of actors. Some practical examples of these applications are described next.

Economic Relevance to Prioritize Decisions

The economic context section of the *Observatories* aims to merge information from diverse sources at various levels to contextualize the crop's economic importance in each region or country, a primary and essential input for scientists and policymakers to prioritize research and investment to address the real needs of farmers (large and smallholder), and other stakeholders. As mentioned before, we extract these inputs mainly from open datasets that, although helpful, still require extensive work to merge the needed information and could misguide certain conclusions unless a clear understanding of the crop context is given.

Cassava was considered the fourth most important primary product and diet component of more than one billion people around the world (Aristizábal and Sánchez, 2007), as well as the third most important source of dietary energy for developing regions of the world (Ceballos et al., 2012). Furthermore, the so-called Rambo Root has been listed as a crop with high potential to fight hunger and cope with climate change variability (Villarino et al., 2020). Nonetheless, available data rank cassava as the 13th most crucial crop according to area harvested in 2019 worldwide (27 million hectares), well below the three top-ranked crops (i.e., wheat: 216; maize: 197; and rice: 162 million hectares), a place it has held with slight variation in the last decades. However, the crop's importance is underestimated, since we are comparing a crop that is suitable for the tropics against agricultural production in both temperate and tropical regions, diminishing the importance of the crop and affecting its prioritization for development. In agriculture, the relevance of the crop location matters when we assess its economic importance (Joglekar et al., 2016).

The literature that discusses cassava's economic relevance and evolution is limited. Previous studies go back to the late 1980s, when De Bruijn and Fresco (1989) identified a decline in cassava's global importance. Nowadays, assumptions and knowledge are acquired through the experience of crop researchers on the major contributions that cassava could provide; however, this information is not often accessible for the public nor necessarily grounded in data. Hence, the *Cassava Lighthouse* gives insights into the role of this crop, being an opportunity to demonstrate its relevance for tropical agriculture. When we restrict the analysis to tropical areas, cassava is ranked ninth, not that far from the top-ranked crops.

If we factor in different regions, we observe that cassava was the third most important crop for sub-Saharan Africa (SSA) in 2019, competing with millet, the crop having that place in past years (**Figure 1**). Meanwhile, in South and Southeast Asia and the Pacific (SSEA&P), cassava was the 18th crop in 2019, but, for Thailand, Cambodia, Laos, and Vietnam, it is of major importance, ranking fourth, second, and sixth (in both Laos and Vietnam), respectively. If we consider the value of production, the position of the crop improves substantially, reaching fifth place for the tropics for 2018, first for SSA, and tenth for SSEA&P, thus showing the potential of this crop compared with others to produce higher value in less area. However, it is important to consider that the FAO dataset for value of production is restricted to a limited number of countries for the tropics (70 out of the 103 countries in the tropics had information available for 2018).

Another factor to consider besides area and production value relates to the relevance the crop has within root and tuber crops. According to available statistics for all roots and tubers produced in the tropics, cassava consistently represents more than half of the area harvested (**Figure 2**). In importance, it is followed by yams (19%), sweet potatoes (11%), and potatoes (9%). When compared regionally, 59% of the planted area with roots and tubers in LAC corresponds to cassava, with 57% in SSA and 52% in SSEA&P in 2019 (**Figure 2**). Despite the importance of cassava in SSA, the region had the lowest yield (8.9 tons/ha on average) in 2019, though huge variation exists from one country to another (**Figure 1**). For example, Niger, Ghana, and Zambia present a high yield (more than 20 tons/ha), whereas Burkina Faso, Central African Republic, Equatorial Guinea, and Uganda present yields below 4 tons/ha. These countries could be prioritized areas considering the local importance of the crop, especially for the large share of smallholder cassava producers around the world.

The information displayed in the cassava observatory will facilitate the process of identifying, evaluating, and targeting the above aspects according to the research objectives, and by shifting between levels of analysis (regions, countries, and departments) depending on data availability. Furthermore, disaggregated information will be more likely found for the countries where cassava plays a significant role, one of the advantages of the "crop approach" followed by the *Observatories*.

Crop Quick Response to Crisis Context

Beyond being an open information platform on specific crops, the *Observatories* have focused on generating research products derived from data collection and strategic alliances with partners. Thus, in the context of the health crisis, the *Rice Observatory* conducted a quick participatory assessment on the effects of the COVID-19 pandemic across the Latin America and the Caribbean rice sector (Urioste et al., 2020). The objective was to evaluate the impact of the pandemic on the rice sector regionally during the first 2 months of confinement (March and April 2020).

Unlike other agricultural commodities such as soybeans, meat, and maize, whose prices fell due to the drastic drop in demand for meat and biofuels, the main international reference prices increased considerably for rice. This increase was mainly because of export restriction policies implemented by some of the

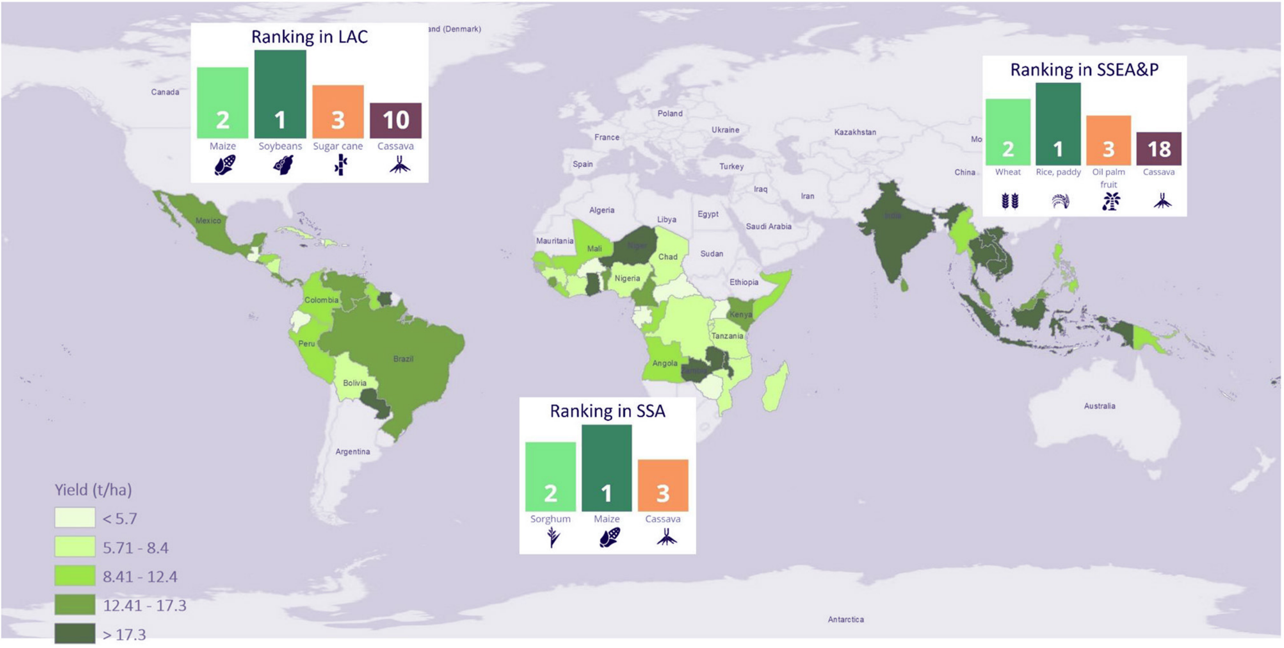


FIGURE 1 | Yield map per country and regional rankings on cassava relevance by hectares harvested 2019. SSA, Sub-Saharan Africa; SSEA and P, South and Southeast Asia and the Pacific; LAC, Latin America and the Caribbean.

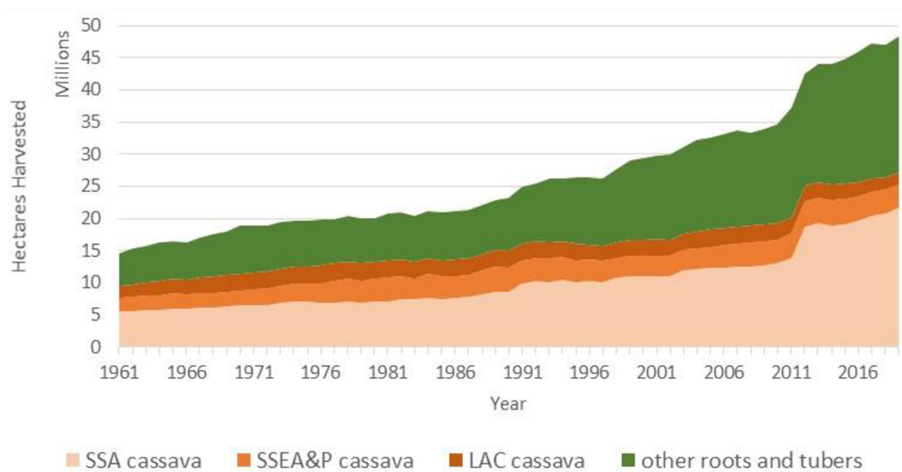


FIGURE 2 | Historical total root and tuber area harvested and cassava area harvested by region. SSA, Sub-Saharan Africa; SSEA and P, South and Southeast Asia and the Pacific; LAC, Latin America and the Caribbean. Other roots and tubers include everything else besides cassava.

world's major exporters (Cambodia, Myanmar, India, Thailand, Vietnam) amid fears of a decrease in stocks due to the sharp increase in demand. In the case of Latin America, rice imports from these origins are limited. Despite the increase in demand for non-perishable foods and the consequent effect on prices, it was not possible to visualize the effects of the pandemic on the rice sector regionally by that time (**Figure 3**).

A total of 40 surveys were collected from opinion leaders and stakeholders from the rice sector in 20 countries. Most countries reported some effect on the sector, with restrictions on the movement of people and transportation of products being the most recurrent problems, although the agricultural sector was exempt from these restrictions in most countries. In contrast, countries also reported positive effects throughout the period, with increased demand and prices being the main drivers. At the same time, major exporters benefited not only from higher prices but also from the opening of new markets left unattended following the restrictions imposed by Asian exporters. Furthermore, the pandemic became an opportunity to highlight the importance of the sector and encourage

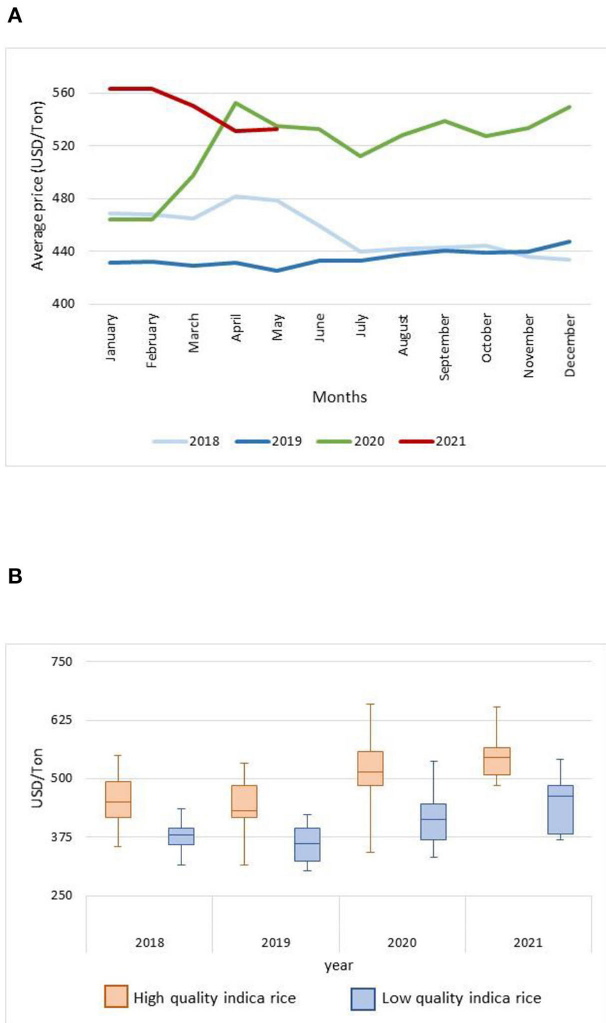


FIGURE 3 | Price trend for all kinds of rice products during COVID-19. **(A)** Yearly trend of average high-quality indica rice price before and after COVID-19. Average international price of reference (monthly) for selected High-Quality Indica Rice (United States Long grain 2.4%, Uruguay Long grain 5%, Thailand 5% broken, Thailand Parboiled 100%, Thai 100% B, Vietnam 5% broken). After COVID is considered past 2020. **(B)** International reference range of prices for high- and low-quality indica rice before and after COVID-19. Graph-box presents maximum and minimum prices at the end of the box and median at the center accompanied by percentiles 25 and 75% for the upper and lower box boundary. Average international price of reference (monthly) for selected High-Quality Indica Rice (United States Long grain 2.4%, Uruguay Long grain 5%, Thailand 5% broken, Thailand Parboiled 100%, Thai 100% B, Vietnam 5% broken) and Low-Quality Indica Rice (Vietnam 25% broken, India 25% broken, Pakistan 25% broken, Thailand 25% broken, and Thai A1 Super). After COVID is considered past 2020.

governments to implement a series of policies to support the sector, which we also compiled and analyzed in the framework of this work (Urioste et al., 2020).

These results were disseminated through two regional webinars, one focused on the presentation of preliminary results and complemented by the opinions of three regional rice experts, with almost 600 participants from 25 different countries. A final report was prepared and disseminated through FLAR and the Alliance network and displayed in a specific section of the *Rice Observatory*, the COVID-19 Information Hub for the Rice Sector. In fact, the good acceptance of this initiative prompted FLAR partners to request a second survey of information 1 year after its publication in order to capture the impacts that the pandemic has had over the past year and to be able to contrast the information with official statistics on production and commercialization, which to date are already available for most of these countries. We also intend to scale up this sectorial monitoring initiative as an annual exercise for the updating and presentation of data by the *Rice Observatory*. The objective is to produce an annual report that addresses specific topics, a methodology that is also expected to be scaled up to the other *Observatories* to generate research products that can be useful at different levels.

Improved Varieties and Grain Quality

The *Observatories* have worked as a platform to display and link research conducted by multidisciplinary teams within FLAR and the Alliance Bioversity-CIAT. The *Rice Observatory* presents information exclusively generated by FLAR researchers interested in measuring grain quality. Thanks to their collaborative research network, it was possible to collect samples of the different improved varieties of rice in the region. These samples were analyzed by FLAR's Rice Quality Laboratory to determine their main attributes in terms of appearance, grain quality, and indirect rice culinary quality. Those results are displayed in the consumption section, presenting a catalog of 125 varieties from 16 countries.

For the sampled varieties, there are multiple quality indicators such as grain size and shape (length-width ratio), chalkiness, gelatinization temperature, and amylose content, variables that have their own scale of interpretation and contribute to understanding the quality of the rice consumed in the region and comparing improved varieties among the different countries. The variety comparator allows the comparison of grain quality attributes between two varieties in the catalog, not only for comparing categories of variables but also between variables. In addition, scientists collected an extensive repository of quality norms and standards that each member country has for rice. This information is helpful to identify consumer preferences and understand the quality of improved varieties to help producers, consumers, and industry select varieties with higher quality.

Meanwhile, units such as Foresight and Applied Economics for Impact constantly update adoption information on improved varieties. Data collected through our monitoring survey (EMSAL) and diverse open-access datasets are presented through national Rice Briefs that characterize the rice sector nationally. They consider seven key aspects: context of the crop and economic relevance at the national level, production, industry, consumption, policies, technologies, and the most relevant institutions for the rice sector (Urioste et al., 2018; Andrade et al., 2019; Marín et al., 2019a).

Juxtaposing the improved quality of varieties and adoption indicators helps to link producer and consumer preferences to bring lessons for rice breeding programs. This information is usually difficult to collect and access from public information sources. However, the *Rice Observatory* works to bring valuable information to multiple actors in order to interconnect the grain quality characteristics of the most adopted varieties for Colombia, Peru, and Uruguay for which we have information published in the *Rice Observatory* (**Figure 4**). From this, it is evident that a transition exists from adopted varieties and quality indices. In the span of 5 years (from 2014 to 2019), Colombian farmers migrated from Fedearroz 174 and 473 toward Fedearroz 67 and 68, which have higher quality indices for appearance and culinary attributes.

Observatories Networking Around the World

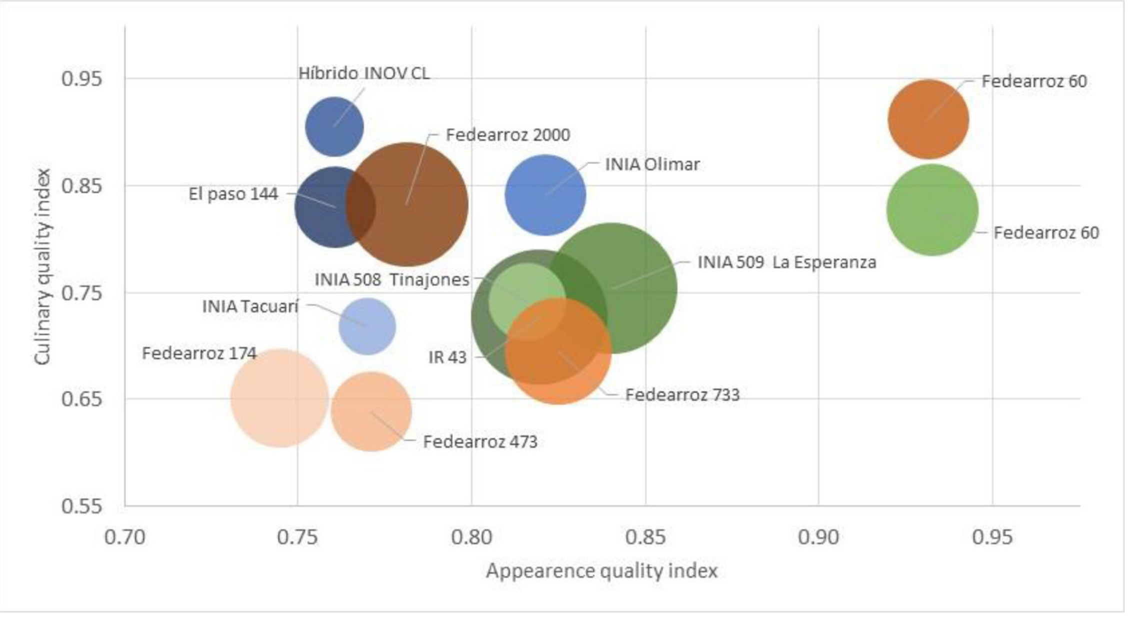
Moreover, the *Observatories* are built upon large networks of public-private-international partners, which are not only a source of information but also extend the network of final end-users that become involved in the data analysis presented by the *Observatories*, hence helping to reach a wider audience, including all types of stakeholders of the different value chains. The duality of the observatory members is relevant, and we are continuously promoting the inclusion of new partners. Currently, the main body of active partners is located in LAC thanks to the support of FLAR, while we expect to add new members in other regions as the other *Observatories* gain traction and become established. We are exploiting the network strengths that the CGIAR has built for decades. For instance, for the *Common Bean Observatory*, we expect to link all the PABRA network, one of the largest research networks in sub-Saharan Africa for common beans. Furthermore, we expect to connect the *Cassava Lighthouse* with all the strategic partners of the Cassava Breeding Program (**Figure 5**).

For the specific example of rice, FLAR brings together diverse organizations (28) that represent 16 countries. All members of this observatory are interested in improving the competitiveness and sustainability of rice production systems by providing technologies to their partners, mainly advanced lines of improved germplasm. These objectives align with the interest of the *Observatories* and contribute to establishing a yearly rice monitoring initiative in the region, with the intent to monitor and help to identify relevant research topics that can contribute to rice producers. The monitoring survey was implemented the first time in 2014 and, up to now, it has helped to collect a set of 34 variables.

In addition to the monitoring strategy across the members' network, the observatory is working hard to display more in-depth information on rice production through diverse household survey datasets that have been collected through diverse efforts. One particular example was the collaborative effort between the Ministry of Agriculture and the National Agricultural Research Institute (INIAP, its acronym in Spanish) of Ecuador to characterize rice production in Ecuador using diverse dataset resources to evaluate whether crop management was changing (Marín et al., 2019b). The *Observatory* in some cases are consolidated as the only sources of open-access information on rice cultivation nationally with that level of aggregation. The *Observatory* became the axis of these data collection efforts to display and deploy relevant information. Some members are currently interested in implementing large initiatives to have monitoring systems at the producers' level that can provide rapid lessons from what is happening in farmers' fields.

Thus, the *Observatory* aims at not only showing the information that has been collected among all the sources, but also at producing additional analyses with this information that can be translated into better information for users, including farmers. This is how the *Rice Observatory* became a web platform managed and funded by the Alliance, RICE-CRP, and FLAR. It relies on diverse member organizations with a wide range of stakeholders and open-data sources containing crop-specific information, and multidisciplinary teams that include economists, software engineers, agronomists, food scientists, plant breeders, and communication experts.

A



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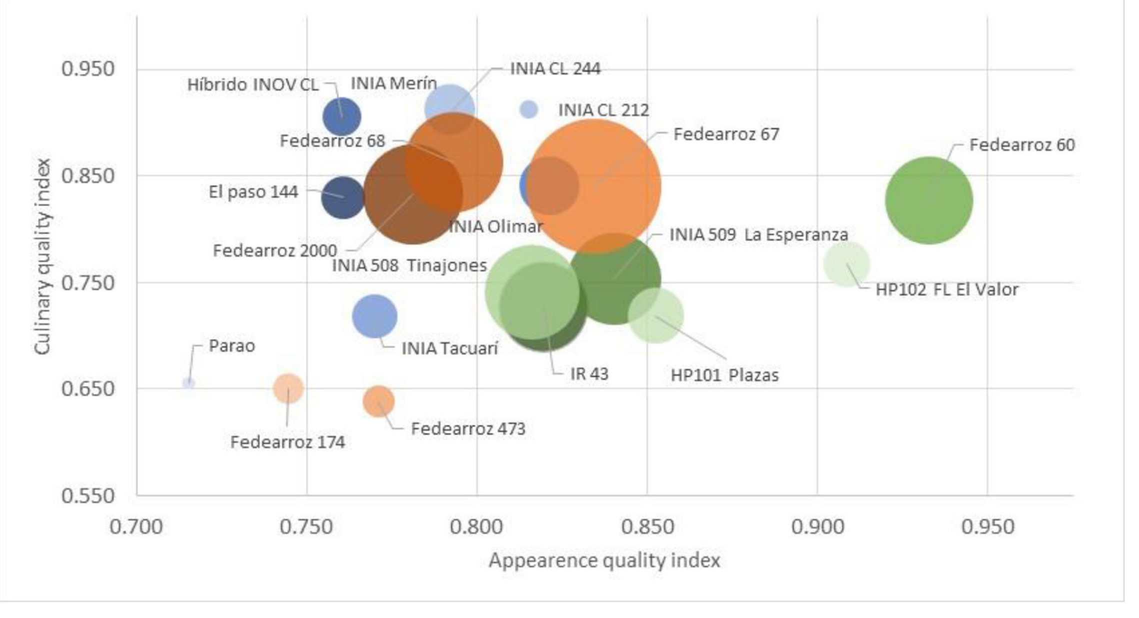

FIGURE 4 | Quality and adoption of improved varieties in Peru, Uruguay, and Colombia, 2014 and 2019. **(A)** Improved varieties adopted in 2014 and grain quality[a]. **(B)** Improved varieties adopted in 2019 and grain quality[a]. [a] Grain quality is calculated in two indices: (i) culinary quality and (ii) appearance quality. Culinary quality is the combination from amylose content and gelatinization temperature. Appearance index is the result of combining chalkiness index, length, and length-width relation. Bubble size represents hectares planted by each variety. Varieties used in Colombia are coded orange, those in Uruguay are coded blue, and those in Peru are coded green.

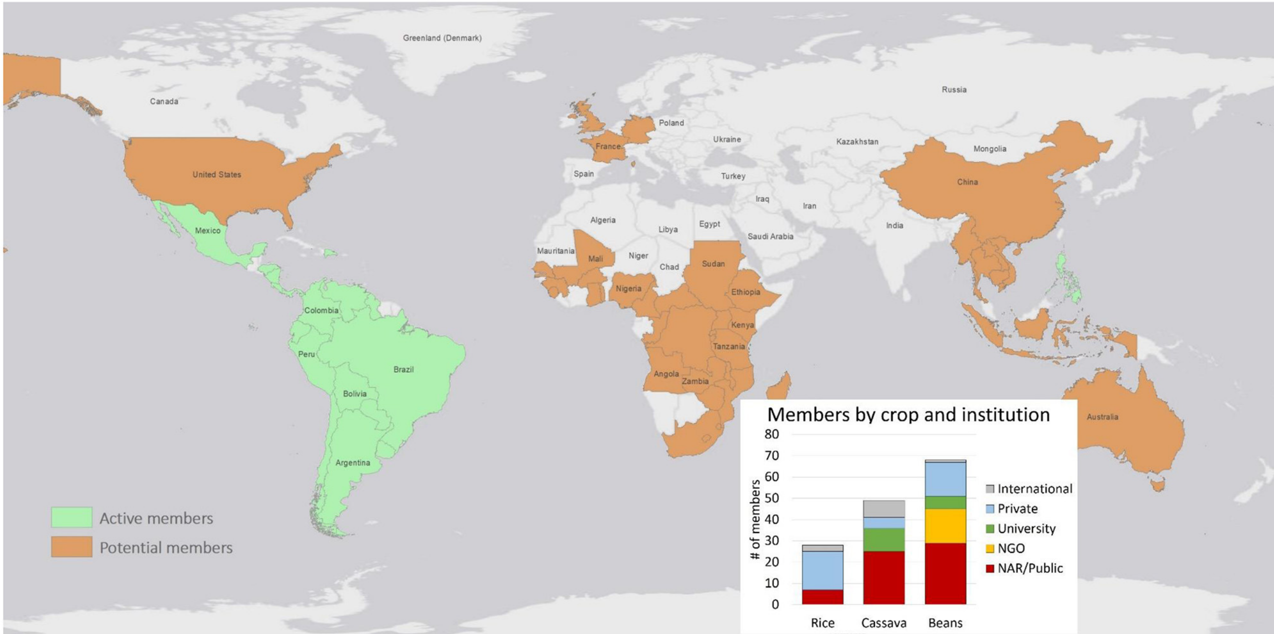

FIGURE 5 | Countries where active and potential observatory partners are located by crop and type of institution, 2021.

DISCUSSION AND CONCLUSIONS

The *Crop Observatories* became an experimental laboratory in which data and analysis fuse to provide multiple data-driven lessons for diverse stakeholders for each crop sector, from scientists to policymakers, and from farmers to consumers. The *Observatories*, aim to identify the relevance of crops in relation to diets, markets, research agendas, climate change, or in relation to other crops. There is a lot of room for further strengthening, since these are just examples of the potential that the *Observatories* have. Nonetheless, multiple lessons still require work and further discussion.

Amid the large number of open-data initiatives, *discrepancies* may arise between databases presenting the same information. For example, Liu et al. (2018) compared country-level cropland areas between FAOSTAT estimates and European Space Agency Climate Change Initiative data, finding substantial differences for many countries between sources. Similar conclusions were found by Pérez-Hoyos et al. (2017), who compared different land cover datasets to examine their potential and accuracy in providing results suitable for monitoring crop areas. Therefore, the question arises as to how to assess the quality of the data presented in the *Observatories* and, in cases in which differences arise between databases, to know how to choose the best available data.

The *Observatories* still need to build a digitally enabled environment, meaning the development of data and application infrastructure, thus platforms and standards that could facilitate the integration and interoperability of initiatives (Porciello et al., 2021). Consequently, existing infrastructure should be harnessed by making it more collaborative and open (Janssen et al., 2017; Wolfert et al., 2017; Porciello et al., 2021), with improved data management practices that increase the value of data properly stored, described, integrated, and shared (Harper et al., 2018). Although the *Observatories* have now entered into a process of automation and harmonization of information to make it FAIRer, there are still many opportunities for improvement.

It is important to generalize the best data management practices as standard operating procedures in the *Observatories* to ensure clear dissemination of the delivered analysis (Janssen et al., 2017; Majumdar et al., 2017), along with periodic communication and transparency between all actors involved (Harper et al., 2018). These actions could be leveraged and further supported by existing global platforms for open data in agriculture, such as the CGIAR Big Data Platform, GODAN, G.E.M.S.®, and Agricultural Innovation Systems (Klerkx et al., 2010).

Moreover, to reach these objectives, it is essential to have human capital with excellent data management skills (Lindblom et al., 2017; Harper et al., 2018). Herein lies the need to provide spaces for updating and transferring the knowledge generated in these processes. On the other hand, the same need to integrate data from diverse sources of information and nature requires concerted work with a transdisciplinary and participatory approach. This to encompass methods for collaborative development and reach a consensus that can translate the data into applications with an impact on society at different levels.

This collaboration should take place not only between scientists of different disciplines but also by integrating other stakeholders such as farmers' associations, industry, service developers, and, more importantly, the final users, particularly smallholders. The authors stressed this multi-stakeholder integration as an essential factor to unleash the full potential and intensification of open data in agriculture, suggesting their participation, not only as passive recipients of technologies but also as co-shapers of these (Janssen et al., 2017; Lindblom et al., 2017; Harper et al., 2018; van der Burg et al., 2019). Thus, it is important to prioritize smallholders, who are the most vulnerable and least likely to benefit from the spillovers of these initiatives if not properly designed and scaled.

Another important lesson relates to funding for the *Observatories*. Although the *Observatories* are fed with open data and even support their infrastructure on open-source platforms, their development and maintenance require resources, which implies the need to find sustainable funding models that allow for their long-term sustainability. The scientists behind the development of these platforms have to develop products and functionalities that respond to the current interests of the funders and, more importantly, the end-users. This is in addition to the crossroads of providing information that is as open as possible, which limits funding schemes with which the cost of the observatory development falls, in part, on the end-users (pay-per-view information).

It is relevant to bear in mind that the existence of the *Observatories* is based on data, so guaranteeing a constant supply of this information is key. Developing business models that are attractive enough for solution providers but that also enable a fair share between the different stakeholders, highlighting the openness of platforms as a tool to empower farmers in their position in supply chains, is really important (Wolfert et al., 2017). Big potential also exists in building business models through producers' associations, considering them as an important source of data and a considerable share of potential users, in addition to the development of public-private-international partnerships to build and maintain national databases that facilitate data sharing, with software products with simple ownership licenses to avoid curtailing initiatives by bureaucracy and other limitations (Janssen et al., 2017; Porciello et al., 2021).

The *Observatories* need to ensure their operability, thus increasing analytical capability and the possibility of integrating with other data initiatives, in addition to implementing big data analytics for data management and processing. For this end, it is important to define clear and complete ontologies for better data integration (e.g., AGROVOC from FAO, CABI's Thesaurus, and the CGIAR crop ontology). The use of visual analytics, a branch of computer science that blends analytical algorithms with data management, visualization, and interactive visual interfaces, is also recommended. Furthermore, it is important to increase forecasting capabilities and integration with agroclimatic advisory services for early warning systems, instead of many ex-post analyses that are currently performed on historical data. The content and interface of the *Observatories* need to become increasingly pragmatic and actionable, with clear relevance to public and private sector incentives.

In summary, this article presents a brief review of open data initiatives and the use of big data for agricultural development, as well as their limitations in terms of access among the various actors in the value chains, with emphasis on the limitations faced by small producers. Crop *Observatories* are presented as one alternative, among many, where diverse efforts are integrated with a transdisciplinary approach, taking into account a wide variety of stakeholders in the process. The results of this collaboration translate not only into the construction of relevant indicators to contextualize the importance of the crop, but go beyond that by integrating diverse initiatives, sources of information and actors to achieve results that would otherwise be difficult to articulate. The list of opportunities is as long as the list of challenges to be faced, but this means room for improvement. Similar initiatives can learn from the experience, and it is hoped that it will serve as a basis for attracting the interest of decision-makers in other crops.

Where is my crop? Perhaps the answer to this question is not limited to a location in space. Harnessing the power of open data and collaborative, multidisciplinary research can give us a better perspective on answers to it. By avoiding missing the forest for the trees, *Observatories* have the potential to become a data-fueled beacon of information, a space where diverse stakeholders come together to share, learn, and create, always with an eye toward making better data-driven decisions. Despite the crossroads of challenges agriculture faces in catching up to this digital revolution, the potential benefits of this new wave can change food systems forever, and for the better. The great challenge lies in how to make these benefits reach the most vulnerable.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession numbers can be found in the article/**Supplementary Material**.

AUTHOR CONTRIBUTIONS

RA conceptualized the study. SU, TR, BS, and FN contributed to conception and design of the study. RA, SU, and TR organized data used. RA, SU, and TR organized data used, perform analysis, and wrote the first draft of the manuscript. BS, FN, JV, LM, KL, and CG wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2021.737528/full#supplementary-material

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Poverty Alleviation Through Technology-Driven Increases in Crop Production by Smallholder Farmers in Dryland Areas of Sub-Saharan Africa: How Plausible Is This Theory of Change?

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The current paradigm of agricultural research and extension in support of rural development in Sub-Saharan Africa (SSA) is to disseminate improved technologies designed to increase the generally low crop yields per hectare on individual farms. Using data from a baseline survey (n = 7,539) from a large rural development programme implemented in five countries in SSA, we calculate the increases in yield per hectare required to significantly contribute to poverty alleviation for households managing such farms. We estimate the gap between current crop productivity and the productivity required to reach a poverty line of $1.90 per capita per day adjusted for Purchasing Power Parity (PPP). We find this gap to be very large, both in percentage and absolute terms. Median additional gross crop productivity required to reach this poverty threshold was: $324/ha/year (254% increase) in Mali; $1,359/ha/year (1,157% increase) in Niger; $4,989/ha/year (665% increase) in Ethiopia; $1,742/ha/year (818% increase) in Burkina Faso; $2,893/ha/year (1,297% increase) in Kenya. The required additional productivity taking account of production costs including the opportunity cost of family labor would need to be even higher. Given that (a) values of net productivity of improved rainfed crop technologies reported in the literature rarely exceed $1,000/ha/year; and (b) the majority of arable farms in SSA are two hectares or less with increasing trends toward land fragmentation, we argue that closing the yield gap among smallholder farmers in SSA will never—alone—be sufficient to meaningfully alleviate the high levels of poverty and deprivation many currently experience.

Keywords: rural development, small farms, intensification benefit index, returns to land, productivity gaps, personal daily income

INTRODUCTION

The current paradigm of agricultural research and extension in support of rural development in Sub Saharan Africa (SSA) acknowledges that smallholder farmers are numerous, widespread and together produce large amounts of food and other produce (Lowder et al., 2016; Ricciardi et al., 2018a). Crop yields per hectare on individual smallholder farms, however, tend to be relatively low (Tittonell and Giller, 2013; Van Ittersum et al., 2016; Ricciardi et al., 2018b; Giller et al., 2021). Yield gaps, the difference between current yields obtained by farmers vs. potential yields obtainable under ideal conditions, exist for all major crops grown in SSA (Van Ittersum et al., 2013; Global Yield Gap Atlas, 2020). Therefore, the current predominant theory of change is that these low yields must be increased substantially to alleviate poverty and increase food security of smallholder farm families, as well as to increase national, regional and global food production (Godfray et al., 2010; Godfray and Garnett, 2014). Many improved technologies have been developed to enable this. New varieties of crops, appropriate input use (e.g., fertilizers, pesticides, and herbicides) and more effective natural resource management techniques have demonstrated impressive percentage increases over farmer practice in yields and profitability per hectare on research stations and in trials in farmers' fields (Harris and Orr, 2014; Devkota et al., 2019). If smallholder farmers adopt these improved technologies and operate them at a farm scale, while maintaining "small plot" levels of efficiency, logic would suggest that both poverty and food security goals can be achieved simultaneously.

However, we know that most arable farms in the world are two hectares or less (Lowder et al., 2016, 2021) and recent evidence suggests that farms of one hectare or less form the majority in SSA (Giller et al., 2021). It is legitimate, then, to ask how much difference these promised large percentage increases in yield per hectare will make to households operating on such small parcels of land? How much will the value of that extra produce contribute to the alleviation of poverty and food insecurity among such households? Although we recognize that poverty is multi-dimensional (e.g., Hellin et al., 2020) we have limited our analysis to consideration of income and consumption.

We attempt to answer these questions using data collected through a baseline survey from a large rural development programme—the Drylands Development Programme (DryDev)—that operated in dryland areas defined as receiving average annual rainfall between 400 and 800 mm, i.e., including "semi-arid" (400–600 mm) and the drier end of "sub-humid" 600–1,200 mm) of five countries in SSA. Crop production is widely practiced in such rainfall regimes, so this 6-year initiative was designed to provide relevant, contextually appropriate support to smallholder farmers in selected dryland areas of Burkina Faso, Mali, Niger, Ethiopia, and Kenya. It sought to facilitate a transition among these farmers from subsistence farming and dependence on emergency aid to sustainable rural development by increasing food and water security, enhancing market access, strengthening the local economy and reducing poverty.

METHODOLOGY

The data that informs this paper were drawn from a baseline survey that was carried out in the latter half of 2015 as part of the DryDev project led by the World Agroforestry Center (Drylands Development Programme, 2015; Hughes et al., 2016). Here, a quasi-experimental impact assessment was implemented. Changes in the status of various socioeconomic and land health indicators were compared between 3,466 households residing in 37 semi-arid sub-catchment sites targeted by the programme and 4,435 other households residing in another 34 neighboring and purposively matched comparison sub-catchment sites. Data from both the intervention and comparison sites were obtained through the administration of a household survey using mobile devices operating on the Open Data Kit (ODK) platform. Stratified proportionate random sampling was used to obtain representative data from targeted smallholder households within these sub-catchment sites. To further obtain representative data on male and female farmers from these households, the gender of each household's respondent was also randomly determined. Given the nature of our analysis in this paper, we pooled these data (collected before any project interventions) from all the surveyed sub-catchments, while excluding households that reported operating no agricultural land, those with missing consumption expenditure or household crop production data. The result is a total sample of 7,539 households, the country breakdown of which is presented in the tables and figures below.

Four main variables from DryDev's baseline survey are used in our analysis: household size, household land size, consumption expenditure per day per capita, and gross annual harvest value. While we acknowledge that the latter three variables in particular are associated with considerable measurement error (Fraval et al., 2019), we argue that it is not large enough to undermine our analysis and the resulting conclusions.

We obtained household landholding size by simply asking each interviewed farmer the size of his or her household's landholdings in locally familiar units, which were subsequently converted into hectares. We are cognizant of the findings of Carletto et al. (2015a) that farmers with small farms tend to overestimate the size of their holdings, while the reverse is the case for those with larger farms. However, given the results of our analysis (see below), we argue that such measurement error would have to be unrealistically large to affect our conclusions.

The second variable we use is daily household consumption expenditure per capita adjusted for purchasing power parity (PPP). We use this variable given that the measurement of global and national poverty, particularly in non-industrialized countries, relies heavily on the data that underlie it (Haughton and Khandker, 2009). To capture these data, several modules adapted from those used in many of the World Bank's Living Standards Measurement Surveys (LSMS) (Grosh and Glewwe, 2000) were integrated into DryDev's baseline survey instrument. We recognize that the timing of such surveys can influence results because consumption, income, etc., are not evenly distributed throughout the year (e.g., Murphy et al., 2012) but, as part of the baseline survey the timing was largely beyond the control of the project. Respondents were asked, in particular, the types of food their households consumed over the previous 7-day period, as well as the quantities. These quantities were then converted into monetary values by asking the respondent how much was paid for each food item or, if the food item was sourced through the household's own production, how much it would have cost if it were purchased from the local market. The respondents were further asked how much they spent on non-food items and services from a detailed list, such as soap, toothpaste, and minibus fares, over the past 4 weeks (regular non-food expenditure). Finally, they were asked about particular "big ticket" expenditures over the previous 12 months from another pre-defined list, such as school and hospital fees, clothes, and home repair (irregular non-food expenditure).

The per capita measure was computed as follows for each household: (1) the weekly cash values of each food item consumed during the past 7 days were added together and divided by seven, thereby estimating the daily cash value of food consumed by the household; (2) household expenditure on items from both the regular monthly non-food expenditure list and annual non-food expenditure list were added together and divided by 30 and 365, respectively, thereby estimating the household's average daily expenditure on regular and irregular non-food items; (3) the daily consumption expenditure estimated for food and the regular and irregular non-food items were then added together and converted into USD adjusted for PPP; and (4) to derive each household's per capita consumption expenditure, its PPP adjusted dollar value was divided by the number of its members (household size).

Finally, data on baseline crop production levels were obtained by asking the interviewed farmers (a) the specific crops their households grew in 2014; (b) the quantity of these crops that were harvested and their cash value at the time of harvest. There is a complex interplay between seasonal changes in prices and potential increases in incomes for farmers who are able and willing to store some or all surpluses (Djurfeldt, 2012), although storage itself may incur additional costs, and consequences would differ for each household so farm gate prices at the time of survey were used for convenience. (c) the expenses incurred in producing and/or marketing each crop (e.g., inputs, labor, and transport); and, finally, (d) the quantity sold, if any. The resulting data for each crop were aggregated to construct several variables, including gross harvest cash value and net harvest cash value. We focus our analysis for this paper on the former for several reasons: (a) while efforts during data collection were made to mitigate double counting crop production and marketing expenses, it is unlikely that these efforts were entirely successful, thereby leading to additional measurement error; (b) only hired labor costs were captured as a possible expense and not that of the interviewed farmer and/or other household members so any shadow prices for family labor were not captured; (c) the gross and net harvest values do not differ considerably for the vast majority of households in the dataset (**Table 1**), thereby indicating minimal costs and/or underreporting (including the value of family labor as mentioned above) and (d) the concept of gross harvest value is closer to the key concepts agronomists use when defining improvements, e.g., increases in yield. To ensure compatibility of this measure with the consumption expenditure per capita measure, we similarly converted the associated figures into PPP using data from the World Bank's website: http://data.worldbank.org/indicator/PA.NUS.PPPC.RF

In order to be able to compare *per capita* household daily income (PDI) from farming with *per capita* daily consumption and with the potential *per capita* daily farm income given the farm size and the household size, we used the following equation (from Harris and Orr, 2014) to calculate current *per capita* household daily income from farming:

$$\text{Mean PDI [\$/person/day]} = \frac{\text{Farm size [ha]} \times \text{Net (or Gross) Return [\$/ha/year]}}{365 \times \text{Household Size}}$$

By setting the PDI to a particular target value such as a poverty "line" and re-arranging the equation slightly we are able to calculate the (gross or net) Required Return to Land ($RR_{1.9}$, \$/ha/y) necessary for a household to cross that line, in this case \$1.90 per person per day (Ferreira et al., 2015). We chose this international value to enable simple cross-country comparisons and we recognize that other targets are possible, such as the living wage (Wage Indicator Foundation, 2021). However, living wage values are usually calculated on the basis of representative families or single individuals and are of limited use in comparing individual households of differing sizes as we have done here. Since living wage values are generally (much) higher than the international poverty line, the latter represents an "easier" target to achieve.

In addition, we calculated an Intensification Benefit Index (IBI)—the rate at which PDI will increase if (gross or net) returns to land increase, by whatever means—which is a measure of the responsiveness of personal daily income from farming to agricultural intensification. IBI is a ratio with units of cents/dollar and so is independent of cost-of-living differences and exchange rates between countries and over time (Harris, 2019). The relation between PDI, annual return to land and IBI is shown schematically for three hypothetical households in **Figure 1**. The point at which PDI crosses the poverty line is the annual return to land required to generate \$1.90/p/d for members of any household with a given number of members and amount of operated land. Changes in household size or land farmed will change IBI. For instance, the hypothetical household in **Figure 1** with an IBI value of 0.39 cents/dollar farms 7.1 ha and has 5 members. If they can only farm 5 ha then their IBI will decline to 0.27 cents/dollar as a consequence of a reduction in potential supply from less land. Conversely, if an additional person joins the household while still farming 7.1 ha, IBI will also fall to 0.32 cents/dollar but as a consequence of increased demand for supporting income. Values of IBI calculated in this paper represent a snapshot in time.

RESULTS

Farm and Household Characteristics and Farm Performance

Farm size per household varied markedly both within and between country samples (**Table 1**). Median farm size ranged from only 0.63 hectares in Ethiopia to 7 hectares in Mali. Mean values were larger than the median in all countries, reflecting the skewed distribution toward smaller farms, and coefficients of variation ranged from 65% for Ethiopia to 120% for Kenya. The percentage of farms of two hectares or less for the whole sample was around 50%, i.e., less than the estimate of 73.8% by

TABLE 1 | Farm size, household size, and crop performance.

Variable		Country (No. of respondents)					
		Kenya (1391)	Ethiopia (1507)	Mali (1393)	Niger (1934)	B. Faso (1314)	Total (7539)
Farm size (ha/HH)	Median	1.21	0.63	7.00	3.00	3.00	2.02
	Mean	1.77	0.71	9.15	3.80	3.99	3.83
	StDev	2.120	0.395	7.243	2.944	4.220	4.882
Farm size (% of HHs)	3 ha or less	85.9	99.9	15.9	55.7	56.5	62.9
	2 ha or less	71.6	99.0	7.5	34.9	34.7	49.4
	1 ha or less	41.9	86.2	3.0	10.1	10.2	29.9
Household size (Total No.)	Median	6.00	6.00	6.00	7.00	9.00	6.00
	Mean	5.90	5.73	6.21	7.86	10.34	7.20
	StDev	2.456	2.046	2.324	3.711	5.363	3.775
Household size (Adult Equivalent)	Median	3.47	2.95	3.73	3.72	4.88	3.48
	Mean	3.53	3.17	3.82	3.97	5.28	3.93
	StDev	1.255	0.877	1.284	1.521	2.368	1.669
Farm size per capita (ha/person)	Median	0.202	0.125	1.631	0.568	0.441	0.333
	Mean	0.347	0.141	1.200	0.429	0.333	0.616
	StDev	0.458	0.106	1.631	0.497	0.428	0.939
Gross crop value ($/HH, PPP)	Median	269	532	1,573	418	756	575
	Mean	631	847	2,920	810	1,109	1,226
	StDev	2,040.9	2,511.2	4,486.1	1,457.9	1,911.7	2,756.2
Gross crop productivity ($/ha, PPP)	Median	224	839	234	131	241	246
	Mean	528	1,231	392	207	335	527
	StDev	1,525.3	3,293.4	1,407.6	321.5	700.3	1,791.4
Net crop value ($/HH, PPP)	Median	165	399	1,236	375	646	445
	Mean	453	686	2,429	719	966	1,022
	StDev	1,889.3	2,500.8	4,241.7	1,363.4	1,862.6	2,604.4
Net crop productivity ($/ha, PPP)	Median	138	641	190	117	206	197
	Mean	377	988	336	182	291	427
	StDev	1,474.0	3,281.4	1,395.5	309.0	688.1	1,761.3

Lowder et al. (2021) for all of SSA. The two East African countries Kenya (71.6%) and Ethiopia (99.0%) had higher proportions of these small farms than the three West African samples: Mali (7.5%); Niger (34.9%); Burkina Faso (34.7%).

Household size varied between country samples less than farm size with a median size of 6 in Kenya, Ethiopia, and Mali (and overall) but 7 in Niger and 9 in Burkina Faso. Median farm size per capita (based on the total number of people in the household) ranged from 0.125 ha per person in Ethiopia to 1.631 ha per person in Mali, with an overall median for the sample of 0.333 ha per person. Mean values ranged from 0.141 ha per person in Ethiopia to 1.20 ha per person in Mali. The mean for the whole sample was 0.616 ha per person and, again, in all countries the median values were smaller than the means, reflecting distributions skewed towards smaller values.

There were large differences between country samples in the value of crops produced per household, with an almost 6-fold difference in median values (and an almost 5-fold difference in mean values) of gross production between those for Kenya and for Mali. However, when expressed on a per hectare basis, median gross productivity was clustered between 130 and 250 $/ha/y, with only Ethiopia being markedly more productive with $839/ha/y. Mean values for gross productivity followed a broadly similar pattern (**Table 1**). Net crop value per household and net crop productivity per hectare were all, as expected, less than their gross counterparts but not by very large margins, suggesting quite small production costs or, more likely, difficulties mentioned earlier in assigning all costs to crop production. Typically, the ratio of net value (when all costs, including all labor, are taken into account) to gross value in maize-based systems ranges from around 40% to 60% depending on management (Kihara et al., 2012, **Table 4**) and can go lower, to around 25%, on low fertility soils (e.g., Guto et al., 2011, **Table 6**).

Income From Crops and Contribution to Household Consumption

Overall, median ($1.27/p/d) and mean ($1.75/p/d) values of consumption were small, and below the poverty line of $1.90/p/d. Country sample median values varied from $0.80/p/d in Burkina Faso to $1.96/p/d in Kenya whereas mean values ranged from $1.02/p/d in Burkina Faso to $2.85/p/d in Kenya (**Table 2**). Overall, crop gross value contributed only 19.2%

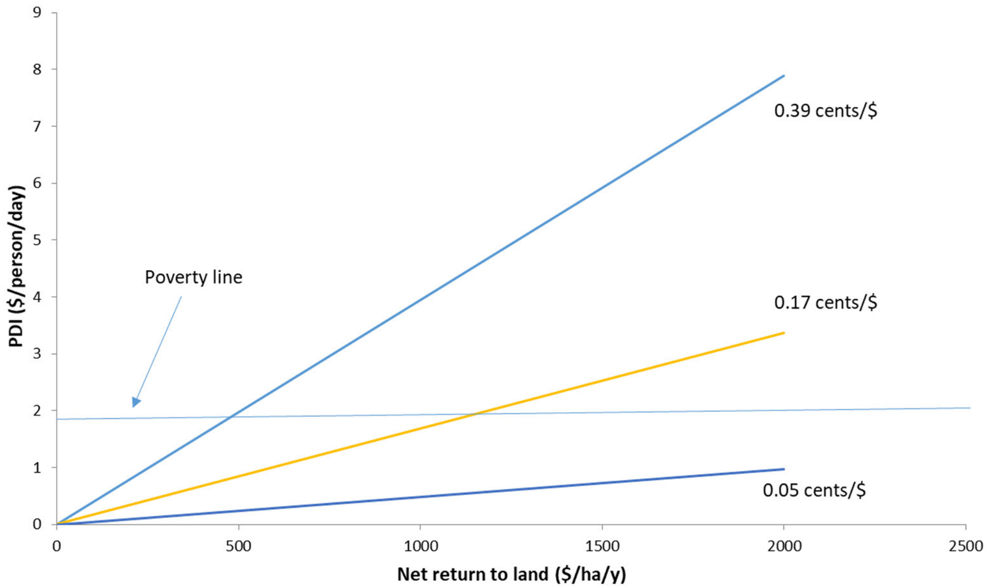

FIGURE 1 | Relation between personal daily income (PDI) and annual returns to land for three exemplar households that vary in size and farm size. IBI is the gradient of the line for each household and the International Poverty Line of $1.90 per person per day is also shown.

TABLE 2 | Household consumption ($ per person per day), the percentage contribution of gross- and net crop contribution to it and the percentage of households for which crop production meets or exceeds it.

Variable		Country (No. of respondents)					
		Kenya (1391)	Ethiopia (1507)	Mali (1393)	Niger (1934)	B. Faso (1314)	Total (7539)
Consumption ($/p/d, PPP), TN	Median	1.96	1.52	1.49	0.96	0.80	1.27
	Mean	2.85	1.77	1.98	1.26	1.02	1.75
	StDev	3.545	1.721	2.011	1.392	0.855	2.161
Gross crop contribution to consumption (%)	Median	7.1	18.5	49.3	16.8	26.3	19.2
	Mean	15.1	31.2	101.4	28.6	39.6	42.0
	StDev	78.15	78.41	198.49	43.14	71.41	108.87
Households achieving or exceeding consumption (%)		0.9	3.8	24.6	3.9	4.4	7.3
Net crop contribution to consumption (%)	Median	4.4	13.2	39.6	14.8	22.8	15.6
	Mean	11.6	25.9	82.1	25.6	34.9	35.2
	StDev	77.85	77.64	177.68	41.30	70.25	100.00
Households achieving or exceeding consumption (%)		0.7	3.2	19.7	3.1	3.8	5.9

to median household consumption (ranging from 7.1% in Kenya to 49.3% in Mali) and in only 7.3% of households did it contribute to 100% of their consumption (range 0.9% in Kenya to 24.6% in Mali). On the basis of net crop value, contributions to household consumption were lower still, with even fewer households (0.7% in Kenya to 19.7% in Mali) achieving or exceeding their daily consumption levels. Given that net cropping income values are likely to be overestimates because the value of family labor was not considered, actual contributions to consumption will likely be reduced even further in real terms.

Income From Crops and Contributions to Crossing the Poverty Line

Gross crop production contributed only small proportions of the value required for households to achieve $1.90/p/d, with median values varying from 7 to 15% and only in Mali with 38% did it contribute more (**Table 3**). Except for Mali, where gross crop production value exceeded the poverty line in 19% of households, only a small proportion (1.4–2.3%) of households in the other four countries had reached the line with gross crop income. Net values (but excluding the opportunity cost of family labor) were all correspondingly smaller but varied in a similar pattern.

TABLE 3 | Gross and net crop contribution toward generating $1.90 per person per day.

Variable		Country (N)					
		Kenya (1391)	Ethiopia (1507)	Mali (1393)	Niger (1934)	B. Faso (1314)	Total (7539)
Gross crop contribution to poverty line (%)	Median	7.4	14.6	38.0	8.5	12.2	12.7
	Mean	18.4	24.0	71.7	17.4	17.0	28.9
	StDev	74.44	62.48	119.23	33.99	31.85	72.96
Households achieving or exceeding poverty line (%)		2.2	2.0	19.0	2.3	1.4	5.1
Net crop contribution to poverty line (%)	Median	4.3	10.6	30.1	7.4	10.3	10.0
	Mean	13.5	19.6	59.6	15.5	14.9	24.0
	StDev	73.42	61.87	110.27	31.71	31.02	68.71
Households achieving or exceeding poverty line (%)		1.7	1.7	14.7	2.1	1.0	4.1

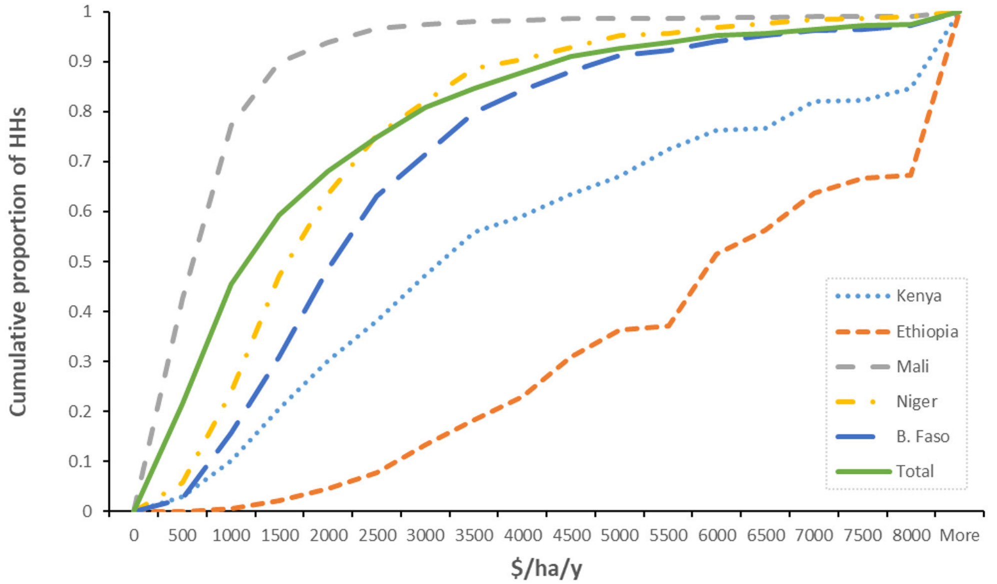

FIGURE 2 | The proportion of households that require a given agricultural return ($/ha/y) to generate a personal daily income of $1.90 per person per day.

Median- and mean crop productivity per hectare were very low in all country samples except, perhaps, in Ethiopia (**Table 1**) and crop production was not contributing very much toward current household consumption (**Table 2**) or to reaching the poverty line (**Table 3**). **Figure 2** shows the proportion of households in each country sample that require a given net agricultural return ($/ha/y) to generate a personal daily income of $1.90 per person per day.

The median additional gross crop productivity required to generate $1.90/p/d for successive quartiles of households is shown in **Table 4** while the percentage increase over current productivity which that represents is shown in **Table 5**. Although it is difficult to generalize about the feasibility of achieving these additional levels of productivity because they are composite values comprised of different crops and prices aggregated for each household, gross productivity in these terms is broadly proportional to "yield." At first glance the value of 713 $/ha/y for the 25th percentile of the overall sample (**Table 4**) seems achievable. However, this represents a 365% increase in "yield" over the current cropping performance (**Table 5**). Ethiopia requires the same 365% increase in productivity from a base that is already relatively high at $839/ha/y (**Table 1**) and Kenya, Niger and Burkina Faso all need to increase gross productivity by over 500%. Even Mali needs to more than double productivity. The large percentage increases in gross productivity noted above are just for the first quartile (least needy) of households and the necessary increases become even larger for successive quartiles, with the 50th percentile of households in Kenya and Niger requiring increases of more than 1,000%. For the 75th percentile, all countries except Mali (where over 500% increase is required) need to improve gross crop production by 1,500–3,500%. Required increases in net productivity are even greater than for gross increases (data not shown).

TABLE 4 | Additional (by quartile of households' required increase) gross crop productivity ($/ha/y) required for households to generate $1.90 per person per day.

Country	Household percentiles			HHs already generating $1.90/p/d
	25	50	75	%
Overall	713	1,722	3,902	5.15
Kenya	1,422	2,893	5,554	2.16
Ethiopia	3,021	4,989	7,838	1.99
Mali	72	324	665	19.02
Niger	811	1,359	2,342	2.33
B. Faso	1,019	1,742	2,868	1.37

TABLE 5 | Percent increase in gross crop productivity required (by quartile of households' required increase) for households to generate $1.90 per person per day.

Country	Household percentile		
	25th	50th	75th
Overall	365	769	1,786
Kenya	598	1,297	3,537
Ethiopia	365	665	1,433
Mali	122	254	540
Niger	546	1,157	2,662
B. Faso	514	818	1,494

Intensification Benefit Index of Households

The second metric used in this paper, IBI, describes the rate in cents per dollar at which household members will benefit from productivity increases (Harris, 2019), and its distribution within each country sample is shown in **Figure 3**. The distribution is negatively skewed for all countries except Mali, reflecting the larger median and mean per capita land values for that country (**Table 1**).

Gender Differences

Overall, only around 9% of households were headed by women, ranging from 4% in Mali and Niger, 7% in Burkina Faso, 9% in Ethiopia but 20% in Kenya (**Table 6**). While it is difficult to be definitive about such relatively small samples, the median value of household size for male-headed households tended to be larger than for female-headed households by around 20% in Kenya and Mali, by around 40% in Niger, by 50% in Ethiopia and by 100% in Burkina Faso. In contrast, median farm size of male-headed households overall was about twice that of female-headed households although this difference was not consistent across countries, with little difference in Kenya and Ethiopia, small differences in Mali and Niger but a large difference, around 100%, in Burkina Faso (**Table 6**). Values of consumption per capita did not differ substantially in relation to gender in any country and trends were inconsistent. Gross- and net crop productivity were remarkably consistent by gender within countries.

Because female-headed households tended to have less land but also smaller households, the median values of $RR_{1.9}$ did not differ as much as one might have expected. Although overall female-headed households required 23% higher productivity to reach the poverty line than male-headed households, this was predominantly due to a large gender gap in Ethiopia. Percentage differences were much smaller in the other countries, ranging from no difference in Kenya to 16% in Niger. Similarly, and for the same reasons, values of IBI, though small, were the same (0.06 cents/dollar) for men and women in Kenya and actually higher for women than for men in Ethiopia (0.05 vs. 0.03), Nigeria (0.14 vs. 0.12), and Burkina Faso (0.10 vs. 0.09). Only in Mali, where overall IBI values were highest, did men have higher values (0.33 vs. 0.30).

DISCUSSION

Crop productivity per hectare was very low and there would seem to be opportunities for project interventions to raise it, even in Ethiopia where productivity was much higher than in the other four country samples. This difference requires some explanation. Median and mean farm size in Ethiopia is the smallest of the five countries and there is some evidence in the literature that the relation between productivity and farm size is U-shaped, because operations on very small farms can be much more efficient (Carter, 1984; Carletto et al., 2013, 2015a). The productivity advantage of small farms is also likely to be exaggerated when family labor is not accounted for, as here.

The project targeting was successful in that households in the five countries were predominantly poor with median and mean consumption estimates below the World Bank poverty line (Ferreira et al., 2015). The actual contribution of crop production to household consumption was mostly small (and was likely smaller still given the uncertainties surrounding production costs) except, perhaps, for Mali where the median gross contribution was almost 50%.

The proportion of very small farms, i.e., those two hectares or less, of just under 50% was lower for the overall sample than estimates of the average for SSA as a whole (e.g., 74% by Lowder et al., 2021, **Figure 2**, Appendix A) but was higher in the two East African samples and lower in the three West African ones. Farm size tends to be larger in less productive areas and where population pressure is less, and it is a matter of judgement whether farm size distribution in this survey can be considered representative of SSA. Nevertheless, there is a huge number of farms in SSA smaller than 5 hectares; 50,834,728 according to Lowder et al. (2021), **Table 2**, Appendix B, comprising 92.7% of all SSA farms. Given the closed relation between farm size, family size, and personal daily incomes, the prospects for taking those farmers out of poverty through crop-, or even farm-, production alone must be slim.

Consumption would have been supported by sources of income other than from crop production. Unfortunately, we do not have detailed information about these other activities. However, substantial proportions of the households in each country indicated, by answering the question "Did anyone from your household do any of the following (livestock production;

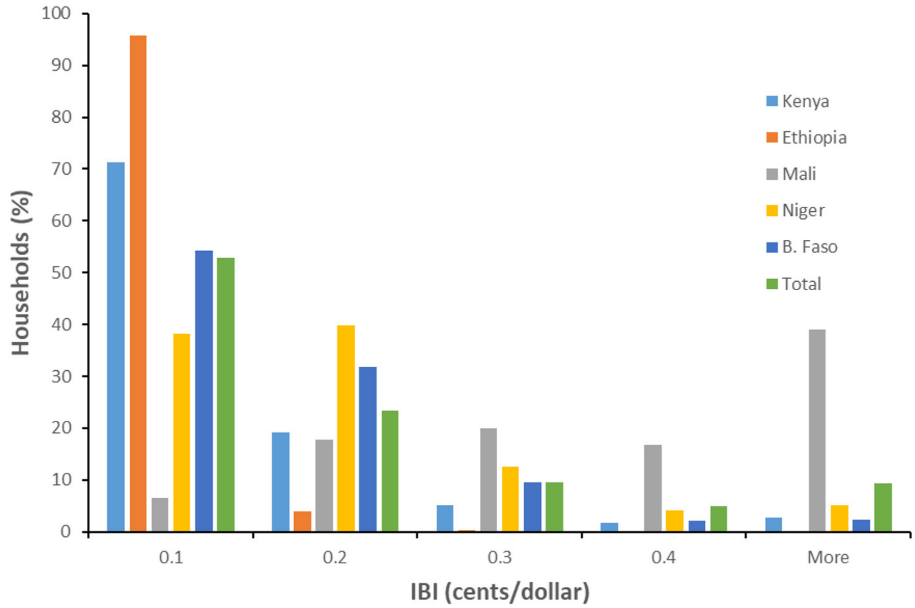

FIGURE 3 | The proportion of households with a given Intensification Benefit Index (cents/dollar).

TABLE 6 | Median household characteristics and agricultural performance by country and by gender.

Variable	**Country**											
	Kenya		**Ethiopia**		**Mali**		**Niger**		**B. Faso**		**All**	
	♂	♀	♂	♀	♂	♀	♂	♀	♂	♀	♂	♀
Sample size	1,116	275	1,374	133	1,331	62	1,852	82	1,217	97	6,890	649
Household size	6.00	5.00	6.00	4.00	6.00	5.00	7.00	5.00	10.00	5.00	7.00	5.00
Consumption, $/p/d	1.99	1.79	1.51	1.45	1.49	1.50	0.96	1.05	0.81	0.65	1.26	1.40
Gross crop prod., $/ha/y	230	215	816	849	234	233	132	108	243	195	246	258
Net crop prod., $/ha/y	140	114	610	699	190	183	118	95	210	180	197	193
Farm size, ha	1.2	1.2	0.6	0.7	7.0	6.0	3.0	2.5	3.0	1.5	2.5	1.2
IBI, cents/dollar	0.06	0.06	0.03	0.05	0.33	0.30	0.12	0.14	0.09	0.10	0.09	0.07
$RR_{1.9}$ $/ha/y	3,427	3,427	5,548	4,161	578	632	1,618	1,387	2,081	1,849	2,081	2,561

off-farm, casual or formal work) in the last 12 months," that this was the case. The proportion of households involved in some form of livestock-related activity ranged from 55% in Niger to 91% in Kenya. Although livestock keeping was quite common, the proportion of households owning more than two cattle ranged from 13% in Ethiopia to 27% in Mali (data not shown) and suggests that our original assumption that these were not livestock-intensive areas was reasonable. Those households involved in some form of off-farm work ranged from 27% in Mali to 81% in Kenya (data not shown). Broadly speaking, the mean percentage cropping contribution to household consumption of each country was inversely proportional to the proportion of households reporting engagement in off-farm work.

We have used two measures of possible impact on household prosperity of improvements in crop production. Both require only three variables related to households. Two (farm size and household size) are relatively easy to collect through surveys although it should be noted that difficulties may be encountered (Carletto et al., 2015b; Fraval et al., 2019) and care is required in defining exactly what the two terms mean in any given circumstance, e.g., what constitutes a household and to what extent land is utilized. Field area can now be measured using a variety of GPS-enabled smartphone apps, a development that should improve data quality in the future. The third variable, net or gross profitability per hectare per year, is more difficult to measure. Few datasets exist that have detailed estimates of actual net crop (or livestock) profitability on farms in developing countries, particularly on a whole-farm basis rather than for individual crops, and we would urge greater research effort in this area. Having said that, once collected on a large scale these three variables can be of immense value in targeting and planning development interventions both within and beyond agriculture.

Both measures assume equitable benefits within households which may not always be the case (Quisumbing and Maluccio, 1999; Anderson et al., 2017; Acosta et al., 2019), but this is a reasonable assumption in the absence of more detailed data on intra-household dynamics that is both expensive to collect and difficult to interpret. Both also, in this paper, use the total number of individuals as the measure of household size, rather than Adult Equivalents because the international poverty line is defined per person rather than per adult equivalent (Ferreira et al., 2015). Using adult equivalents in the calculations reduces the number of "units" in any household to be supported by income, thus lowering thresholds for success and giving a more optimistic scenario. So, for example, a value of $RR_{1.9}$ of \$2,000 per hectare per year for a household in Kenya, based on adult equivalents is approximately equal to \$3,175 per hectare per year based on the total number of people in the household. Conversely, an IBI value in Mali of e.g., 0.31 cents per dollar based on adult equivalents would be around 0.20 cents per dollar when all individuals are counted.

The first measure, $RR_{1.9}$, is the level of production required to take household members above the specified poverty line of \$1.9 per person per day. Together with estimates of current income or consumption, we can then define the size of the task at hand, i.e., the gap in crop productivity or profitability that needs to be closed to move households across the poverty line. **Figure 2** and **Tables 4**, **5** show that very high levels of returns per hectare per year would be required to generate a personal daily income of \$1.90 per person per day for large proportions of the samples from all countries.

We know crop productivity at baseline, and we have calculated the size of the "yield" gap between this and the levels required to support consumption of \$1.90 per person per day, both in absolute terms ($RR_{1.9}$, **Table 4**) and as a percentage of current productivity (**Table 5**). The increases required are substantial, ranging from 122 to 3,537% depending on the country and the quartile of each population (**Table 5**). It should be noted that **Tables 4**, **5** are based on required increases in gross productivity and that targets based on net productivity, i.e., considering all costs of production, including the opportunity cost of family labor—important for smallholder rural households that generally pursue diverse livelihoods (Harris and Orr, 2014; Giller et al., 2021)—would be higher still and so even more difficult to achieve. It should also be noted that \$1.90/p/d is not an ambitious measure of prosperity, representing as it does very low levels of welfare and well-being.

Now we know the size of the profitability gap, we ask the question "Can our proposed interventions, if adopted, close this gap?" Unfortunately, there is limited information concerning the net returns to land of the project interventions. One technology, the construction and use of *Zai* pits—shallow planting basins with organic materials such as manure added and designed to harvest rainwater and improve its infiltration—was widely promoted by the project (ICRAF, 2020) to address the dual objectives of increasing crop yields and reclaiming degraded land. In Kenya, Muli et al. (2017) reported a 167% increase (from 0.9 t/ha to 2.4 t/ha) in the yield of maize when grown in *Zai* pits compared with conventional farmers' practice, although gross margins were only about \$25 per hectare per season due to high production costs. Also in Kenya, Kimaru (2017) measured yield and profitability of sorghum grown in *Zai* pits with various combinations of manure and mineral fertilizer. She reported total gross margins using *Zai* pits over two short-rain seasons and one long-rain season that ranged from minus \$16/ha (i.e., a loss) to \$1624/ha. With two seasons per year in this part of Kenya this gives a crude annual average estimate ranging from minus \$10.7/ha/year to \$1088/ha/year. Conventional planting (not *Zai* pits) with comparable nutrient inputs tended to produce lower yields but were similarly profitable, due to lower production costs. In Burkina Faso, Schuler et al. (2016) reported a small average increase in gross margins (from \$67/ha to \$81/ha) when *Zai* pits were used, with a maximum value of \$169/ha in the case of pearl millet. Returns to labor were less than the local wage rate, although the authors speculated that off-farm opportunities were rare.

The project further promoted a wide range of interventions and training at local- and community levels, some of which are more complicated (and costly) than others but also potentially more profitable. For instance, there was a large programme of training and facilitation in building farm ponds for water collection and storage, thus enabling supplementary irrigation and so broadening the choice of crops to include higher value options. Many farm ponds of varying sizes were built that contributed positively to the livelihoods of multiple households, although it is not clear to what extent each household, or each household member, benefited in net terms (ICRAF, 2020).

Without more information on the economic performance of the various interventions once adopted and operated by farmers it is not possible to analyze in detail the contributions any gains might make to household income. However, based on the limited information presented above on one of them (*Zai* pits), surveys of the literature on the profitability of cropping best practices, e.g., Harris and Orr (2014) and limited data on the performance of various cropping "best practices" in these five countries (Duguma et al., 2010; Mucheru-Muna et al., 2010; Otinga et al., 2013; Badolo, 2017; Elias et al., 2017; Theriault et al., 2018; Issoufa et al., 2020), it is unlikely that even large percentage increases in yield following adoption of improved technologies will significantly increase the income of most households. Crop production increases can improve household food security and nutritional quality and will contribute some progress toward poverty lines, but they are insufficient on their own to take smallholder farmers out of poverty (Gassner et al., 2020).

The second metric used in this paper, IBI, describes the rate in cents per dollar at which household members will benefit from productivity increases and can be used to characterize individual households and communities (Harris, 2019). IBI is particularly useful because, as a ratio of two locally measured values it is independent of differences between currencies and so can be used for comparisons between households or communities in different countries. Because farm size and household size are relatively easy to obtain, IBI could be used to quickly characterize households and communities in relation to how, and to what extent given the potential and limitations of likely interventions, households and communities would benefit financially from their adoption. In

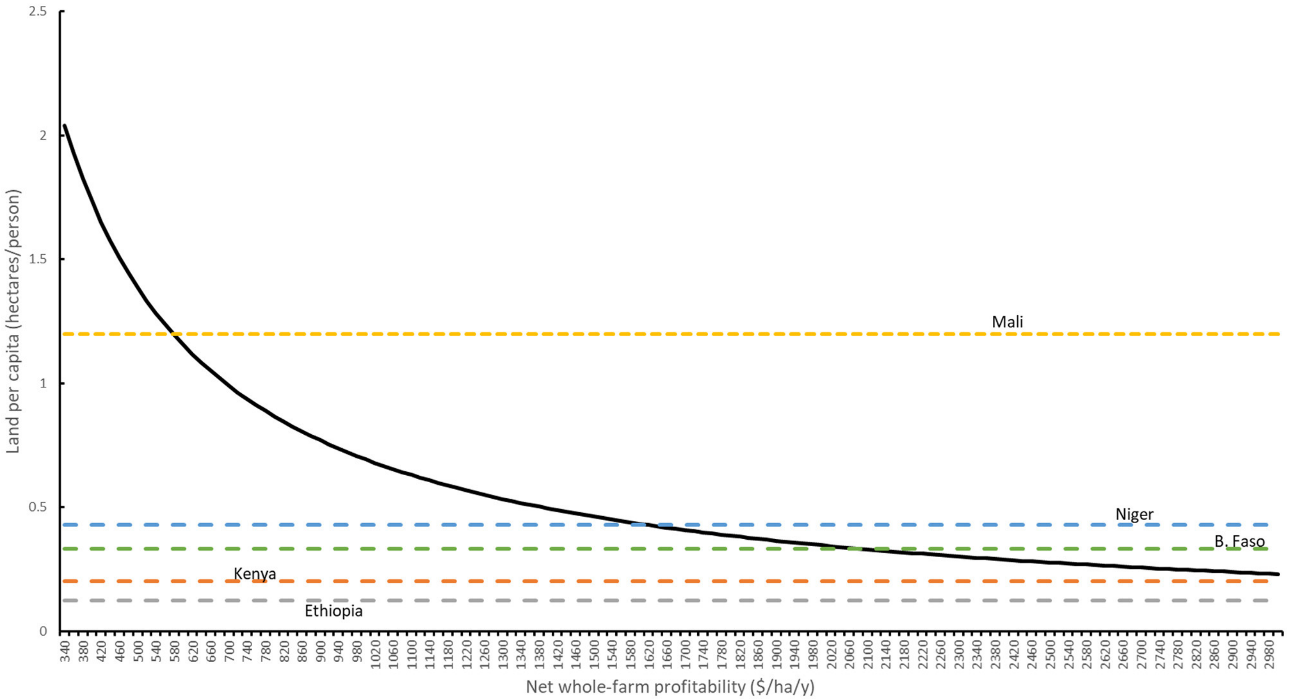

FIGURE 4 | Combinations of land per capita and net whole-farm profitability that will generate an income of $1.90 per person per day. Horizontal lines are the median per capita values for the five country samples.

the absence of changes in household size or farm size, increased returns to land will move households along their particular IBI line (**Figure 1**), resulting in higher PDI values. In theory these lines continue to infinity; in practice limitations of climate, soils, markets, resources, infrastructure, and skills will influence how much the potential of new technologies will be realized and where the "end point" on the line will be for any household. It is interesting to note that IBI values in four of the five country samples were either the same or higher for women than for men. This is counterintuitive in that it implies that female-headed households need not be disadvantaged in the income they would derive from any profitability increases. However, widely acknowledged gender-related difficulties in learning about and effectively adopting improved technologies (e.g., Kilic et al., 2015) mean that such a potential advantage may not be realized in practice.

Although only crop production data were used in this analysis, the form of these two metrics allows the effects of all agricultural production, including livestock, to be taken into account. These data also constitute a baseline against which the effects of project interventions (and other development initiatives) can be measured. The relation between per capita land and the profitability required to reach any given personal income target, in this case $1.90/p/d, is summarized in **Figure 4** and reflects the difference between Mali and the other four countries' samples. The degree of closure of the gap (movement along the x-axis of **Figure 4**) between current performance and $RR_{1.9}$ will be a measure of the effectiveness of agricultural interventions in raising household consumption toward the $1.90/p/d—or any other—poverty line and will enable a degree of partitioning of any effects between technology adoption and changes in farm size and household size.

DryDev—like many other rural development projects—sought to bolster the income, food security, and resilience of the smallholder farming households it targeted. A key pathway that was followed involved the promotion of "improved technologies," such as *Zai* pits and farm ponds. The project impact assessment report (ICRAF, 2020) reveals that this pathway yielded mixed results, a finding that is certainly not atypical of interventions that promote research-informed technologies (Stevenson et al., 2019). However, we have demonstrated in this paper that even if the adoption and resulting effects of improved cropping technologies were realized at optimal levels, the project's transformative impacts would not have been realized. The returns for households with small farms would just be too small.

Small-farm households in these dryland areas are structurally constrained in the degree to which they can improve their livelihoods through crop production. More generally, the limited range of profitability values per hectare using best practice technologies suggests that this is also the case in more productive areas (Harris and Orr, 2014). A recent study involving a larger number of rural households across SSA (Giller et al., 2021) has come to a similar conclusion. Despite these structural limitations there is still potential to bolster smallholder productivity. Our central argument is that the inherent limitations of what can be achieved should be explicitly considered and communicated when devising and promoting such technologies (Berrea et al., 2017). As long as they continue to exist, the majority of smallholder farmers across Africa and other non-industrialized settings will continue to rely on multiple non-farming related endeavors—where they exist—out of sheer necessity. Assuming that farmers will invest additional labor and/or resources associated with improved technologies, even when convinced of their profitability enhancing effects, should therefore not be taken for granted and this theory of change needs to be revisited.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

DH conceived the study, analyzed the data, and wrote the paper. KH designed the data collection exercise and wrote the paper. JO collected and collated the data and wrote the paper. All authors contributed to the article and approved the submitted version.

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Beyond "Women's Traits": Exploring How Gender, Social Difference, and Household Characteristics Influence Trait Preferences

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Demand-led breeding strategies are gaining importance in public sector breeding globally. While borrowing approaches from the private sector, public sector programs remain mainly focused on food security and social impact related outcomes. This necessitates information on specific user groups and their preferences to build targeted customer and product profiles for informed breeding decisions. A variety of studies have identified gendered trait preferences, but do not systematically analyze differences related to or interactions of gender with other social dimensions, household characteristics, and geographic factors. This study integrates 1000minds survey trait trade-off analysis with the Rural Household Multi-Indicator Survey to study cassava trait preferences in Nigeria related to a major food product, gari. Results build on earlier research demonstrating that women prioritize food product quality traits while men prioritize agronomic traits. We show that food product quality traits are more important for members from food insecure households and gender differences between men and women increase among the food insecure. Furthermore, respondents from poorer households prioritize traits similar to respondents in non-poor households but there are notable trait differences between men and women in poor households. Women in female headed household prioritized quality traits more than women living with a spouse. Important regional differences in trait preferences were also observed. In the South East region, where household use of cassava is important, and connection to larger markets is less developed, quality traits and in ground storability were prioritized more than in other states. These results reinforce the importance of recognizing social difference and the heterogeneity among men and women, and how individual and household characteristics interact to reveal trait preference variability. This information can inform trait prioritization and guide development of breeding products that have higher social impact, which may ultimately serve the more vulnerable and align with development goals.

Keywords: social difference, trait preferences, cassava, Nigeria, gender

INTRODUCTION

Public sector plant breeding programs are changing rapidly. Adopting approaches from the private sector, the push toward demand-led breeding has seeded shifts in public sector breeding programs oriented toward food security and social impact. Understanding client needs is critical to demand-led breeding approaches [Demand-led breeding(DLB), 2020], underpinning all subsequent decisions around segmenting and prioritizing target users. Mobilizing "market intelligence," in addition to agroecology and value chain information, breeding programs are expected to develop market segments and associated breeding product profiles [CGIAR Excellence in Breeding platform (EiB), 2020]. While ideologically breeding programs are rapidly evolving to become more demand-led, practically this shift has revealed gaps in evidence and data needed to effectively set market-informed breeding priorities. In the private sector, dedicated and well-resourced marketing units conduct marketing research that is directly used to guide breeding priorities. These are absent in the public sector.

Market research is defined here in a broad sense to cover value chain analysis, product mapping, trait economic values and trait preference analyses, amongst others. Historically the most research attention related to market research in public sector breeding programs have focused on adoption studies and trait preference studies. Capturing trait preferences using methodologically robust and systematic approaches enable breeding programs to develop accurate and impactful product profiles to guide breeding (Ragot et al., 2018). Recent increased attention to trait preference studies on root, tuber and banana crops have enabled breeding programs to unpack breeding priorities in sweet potato (Mwanga et al., 2021), banana (Marimo et al., 2020), and cassava (Bentley et al., 2017; Teeken et al., 2018, 2021). These studies show that distinct use types and social identities, such as gender, shape trait preferences, validating the need for more demand-led approaches and thinking in breeding these historically under-resourced crops.

Understanding trait preferences has involved approaches such as direct ranking (Abeyasekera et al., 2002; Dao et al., 2015; Teeken et al., 2018), or choice experiments (Asrat et al., 2010; Blazy et al., 2011; Acheampong et al., 2018). Most trait preference studies however, do not adequately address social heterogeneity among producers, processors and consumers, despite mounting evidence that social differences matter for varietal adoption. Many studies reported that social differences such as sex, age, marital status and ethnicity affected the adoption of varieties or crops as climate change-adaptation strategies (Acevedo et al., 2020). Trait preferences vary in relation to socio-cultural context and modes of production and processing (Smale et al., 2001), and follow gender divisions of labor and market access, with documented differences in preferences between men and women across crops and contexts (Christinck et al., 2017; Weltzien et al., 2020). These insights may not be relevant for private sector breeding that is mostly concerned with optimizing revenue, but crucial for the public sector breeding for development, that distinguishes itself by explicitly focusing on social inclusion outcomes, such as gender equality, poverty alleviation and food security as laid out in the sustainable development goals.

Gender shapes all aspects of agricultural technology development (Doss and Morris, 2001; Schut et al., 2015). It is therefore critical for breeding programs to consider gender and social differences in seeking to understand market intelligence. Building frameworks and approaches to enable this integration is critical to gender responsive breeding programs (Ashby and Polar, 2019), since the traits a breeder prioritizes in developing a new variety powerfully affects who benefits from the variety, and how (Polar et al., 2021). Gender integration into breeding programs increases their potential to be more impactful (Tufan et al., 2018). As this thinking matures, we move away from homogenous comparisons of men and women, and shift to asking which men and which women. Therefore, it is important to integrate social identities and household characteristics that possibly interact with gender to shape trait preferences to determine the success of new varieties. We chose cassava producing households in Nigeria to explore how gender, social difference, and household characteristics influence trait preferences.

Cassava producing households in Nigeria offer a compelling site of analysis building from a wealth of existing studies. Nigeria has the highest cassava production globally (FAOSTAT, 2021), where it is grown both as a subsistence and as a cash crop. A collection of recent studies explored adoption drivers of cassava in Nigeria (Wossen et al., 2017), and trait preferences for cassava products (Chijioke et al., 2021; Ndjouenkeu et al., 2021; Teeken et al., 2021), including gender analysis of trait preferences (Teeken et al., 2018). The gender differences in trait preferences observed in these studies mainly reflect the gendered roles along the crop value chain. For example, women play an important role in cassava production (Curran et al., 2009; Walker et al., 2014), and perform most of its processing and marketing in Nigeria (Ilona et al., 2017). In the South East and South South regions of Nigeria, women play an important role in cassava production, shifting away from a formerly yam dominant cropping system and as men increase their engagement in non-farm activities (Korieh, 2010; Osuji et al., 2017; Alozie, 2019; Amah et al., 2021).

There is large regional variation in cassava processing and markets in Nigeria. Cassava is mostly produced in the southern part of Nigeria. Gari and fufu are the two major food products produced by smallholder cassava farmers for market and home consumption. Gari is a dry semolina-like pregelatinized granulated flour and fufu is a wet fermented paste obtained by water submersion (Bechoff et al., 2018). Gari is most often consumed as the paste product eba which is obtained by mixing gari with hot water (Bechoff et al., 2018; Awoyale et al., 2021). The South West and North Central zones in Nigeria are relatively more connected to larger scale, urban markets, while in the South East and South South home consumption and regional markets dominate (Abdoulaye et al., 2013, 2015). Cassava based food products and how they are processed differ regionally. In the South West and North Central regions, small- and medium- scale processing centers service households, while in the South East and adjacent parts of the South South cassava is processed within the household (Teeken et al., 2018).

These individual, household, community, and regional variations challenge breeding programs seeking to deliver new cassava varieties to heterogeneous populations of adopters.

Balogun et al. (2021) present the application of a comprehensive survey and analysis methodology package incorporating a novel core adaptive conjoint method (1000minds, 2020), which combines multivariate analysis to capture trait typologies. Trait preferences were asked in relation to the cassava gari value chain. This paper builds from this cassava trait preference study to relate the trait rankings to individual, household, and farm characteristics of respondents collected with an adapted Rural Household Multi-Indicator Survey (RHoMIS) (Hammond et al., 2017). We present results that explore the relationship between trait rankings and individual-, household-, and farm- level characteristics. We build from this to analyze interactions between gender and food security, poverty level, and region to deepen the understanding of how diverse gender experiences drive trait preferences.

METHODS

Sampling

This study followed the sampling strategy of the Cassava Monitoring Survey, which identified states that contribute up to 80% of the total cassava production in Nigeria (Wossen et al., 2017) which are situated in four geopolitical zones of Nigeria: North Central, South East, South South and South West. Close to two-thirds (66%) of total production is in the southern part of the country, while about 30% is in the North Central zone (FAOSTAT, 2021). The second sampling stage involved the selection of two states per zone with the highest cassava production. From these states, sixteen major cassava growing communities were selected based on key informant interviews with Agricultural Development Program (ADP) officers at the state and Local Government Area (LGA) level. Focus group discussions (FGDs) were held in each community with village leaders and community members to capture information on cassava livelihood activities and relevant social groups, as well as verify the prioritized 11 traits. FGDs were further used to determine economic values in the scenarios compared during the 1000minds survey (1000minds, 2020). In the final stage, a list of smallholder cassava value chain actors was compiled. Survey participants were sampled from this list based on their dominant role in the cassava value chain, gender, and social group to ensure representation of all groups with cassava expertise in the communities. More detail of the sampling and FGDs is presented by Balogun et al. (2021).

Survey Implementation

The study was carried out in February and March 2020. Written consent was obtained after participants were informed of the purpose of the study. Ethical approval to conduct the research was granted by the IITA Internal Review Board. A total of 792 respondents participated in the survey (310 men and 482 women). **Figure 1** shows the states covered within the 4 geopolitical zones.

Trait Data Collection

The 11 traits included in the 1000minds survey (1000minds, 2020) were determined based on reports, findings, published research (Bentley et al., 2017; Wossen et al., 2017; Teeken et al., 2018, 2021; Ndjouenkeu et al., 2021) and a literature review (Awoyale et al., 2021). They were also informed by discussions with experts and verified by the community-level FGDs. Trait data collection was based on a pairwise trade-off assessment of 11 cassava traits. We used an online survey tool, 1000minds survey (1000minds, 2020), which follows pairwise comparison of traits based on conjoint analysis that applies the Potentially All Pairwise RanKings of all possible Alternatives (PAPRIKA) method (Hansen and Ombler, 2008). The traits and trait rankings included in the 1000minds survey were defined using parameters calculated as the economic effect of increment per unit change of each trait independently. These parameters were determined during the FGDs. A detailed description of the 1000minds survey (1000minds, 2020) algorithm can be found in Hansen and Ombler (2009). Outputs of the 1000minds survey (1000minds, 2020) assign trait rankings to each respondent ranging from most preferred (1) to least preferred (11) trait for all 11 cassava traits. Trait definitions from FGDs, exact trait level calculations, and details of the methodology are presented in Balogun et al. (2021). Definitions of cassava traits used in this study are described in **Supplementary Table 1**.

Individual and Household Level Data Collection

Household level data were collected using an adapted version of the Rural Household Multiple Indicator Survey (RHoMIS) (Hammond et al., 2017). This study's version of RHoMIS, included the following modules: Food availability, Household Dietary Diversity Score (HDDS), Household Food Insecurity Access Scale (HFIAS), Progress out of Poverty Index (PPI) (Desiere et al., 2015) for Nigeria version 2012 (Schreiner, 2015) and a gender equity indicator. This shortened version was developed together with the creators and data managers of RHoMIS to assure indicators remained valid and could be calculated. This shorter version was developed to decrease the respondents' time burden. Additional variables were collected at the individual and household level to complement the RHoMIS variables for analysis. The full set of variables presented in this study and their definitions can be found in **Supplementary Table 2**.

Analyses

Using SPSS, a Pearson's correlation coefficient (Pearson's r) analysis (Weaver and Wuensch, 2013) was conducted to assess the relationship between traits. The strengths of association were classified as weak (r = 0.10–0.20), moderate (r = 0.21–0.40), or strong (r = 0.41–1.00) and positively (+) or negatively (-) signed. The 1000minds survey (1000minds, 2020) results in trait rankings from 1 to 11, with 1 being most favored. Therefore, a negative association is read as increasing priority for that trait (a rank that increases toward 1) as the associated variable increases, while a positive association infers a decreasing priority for that trait (lowering in rank

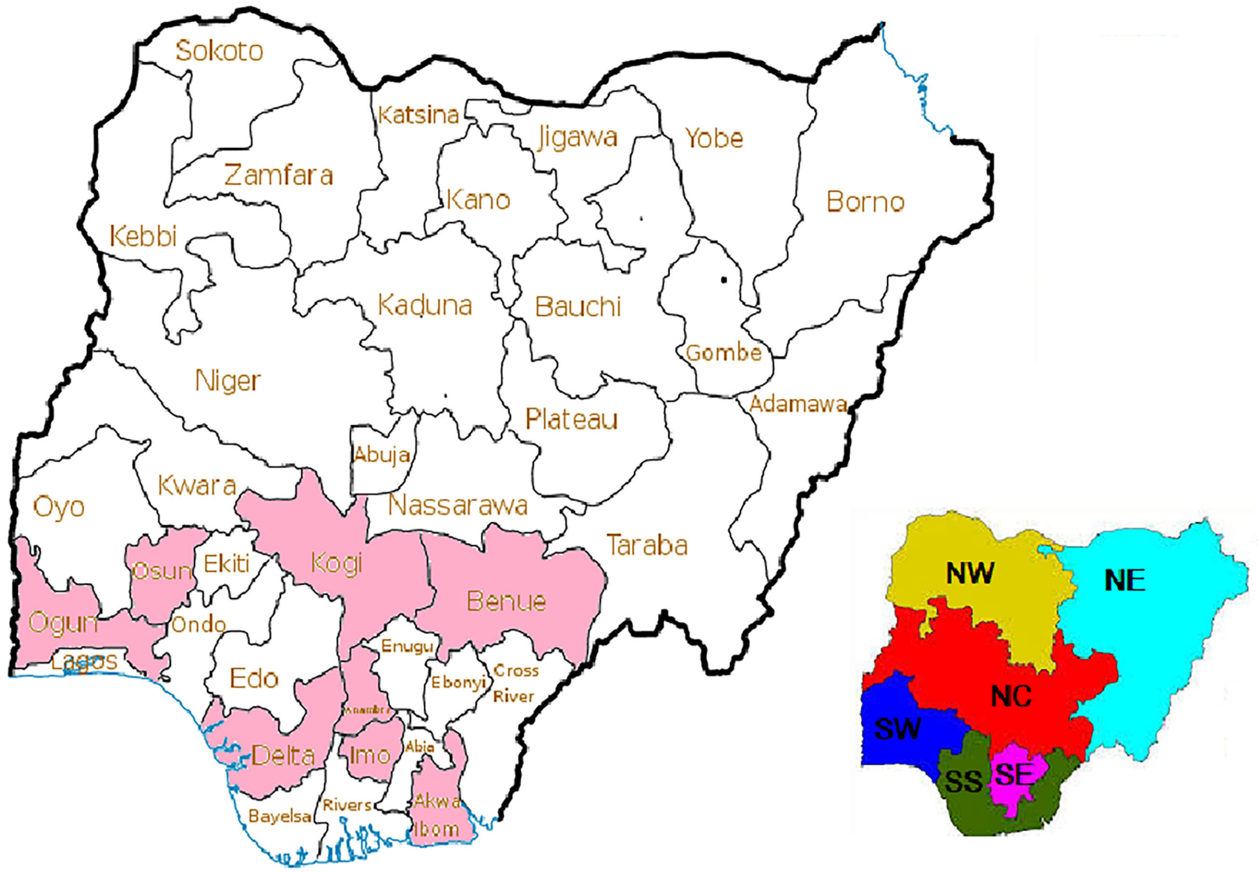

FIGURE 1 | States covered in this study with Ogun and Osun state in the South West (SW), Kogi and Benue state in the North Central (NC), Delta and Akwa Ibom in the South South (SS), and Anambra and Imo in the South East (SE) regions.

toward 11) as the associated variable increases. The results in **Table 1** have been interpreted with this understanding, with the exception of trait mutual correlations. Relationships were considered significant at a probability level of 0.05 (p-value <= 0.05).

For Odds Ratio and Wilcoxon test, the variables for Poverty Probability Index (PPI) and Household Food Insecurity Access Scale (HFIAS) were transformed to binary groups to manage the complexity of the interactions in the analysis. For interpreting the PPI scores (0–100), the poverty likelihood 2011 lookup table (Schreiner, 2015) was used as $1.90 per day purchasing power parity (PPP) 2011 poverty line to convert PPI score to poverty likelihood percentages (PPI index). According to this table 100–95.4% of all the respondents with a PPI score of 10 or lower are classified as poor. Therefore, respondents with a PPI index below 10% were grouped as "poor," and those with a PPI above 10% as "non-poor." For HFIAS, the four categories generated were transformed into two categories: "food secure" and "food insecure" (combining mildly food insecure, moderately food insecure and severely food insecure). Reducing the HFIAS categories was necessary due to the unequal distribution of respondents in each, but doing so could potentially mask more nuanced analysis of the impact of food security on trait preferences.

A cumulative logit model using Procedure Logistic in Statistical Analytical System (SAS 9.4, Cary, NC, USA) was used to investigate the effects of different social variables on trait prioritization. All the traits were ordinal responses (rank of 1–11). Our model response profile is associated with a higher ordered value (lower rank) hence we modelled the probability of prioritizing each trait less (rank of 12). Odds Ratio, Maximum Likelihood Estimates, and Chi-square test (95% confidence interval level) were the metrics used as measure of association. For each of the groups modelled, we considered women (Gender), poverty index below 10% (PPI), and Food secure (HFIAS) levels as our comparison group. Furthermore, we investigated the different possible comparisons between the four regions in Nigeria: South West, South South, South East, North Central. In other words, we investigated the probability of prioritizing a trait by men with reference to women and so on. Wilcoxon rank-sum test was conducted using the wilcox.rank function in base R package of R statistical software version 3.5.2 (R Core Team, 2018) to test for gender differences in trait prioritization between the groups.

RESULTS

Through these analyses, we demonstrate the importance of considering social difference through multiple approaches. We argue that this layered approach to analysis improves opportunities to triangulate results and capture richer trait preference data to inform inclusive product profile development. By starting at the highest level, the relationship between traits, we set the stage for how trait preferences could be understood without recognizing socio-demographic and geographic variables. However, correlations that include these variables, as well as the interactions between these variables, demonstrate that their inclusion will result in more accurate breeding decisions. Finally, a heatmap supports these observations by visualizing the how gender, food security, poverty, and geography can be brought together to identify trait preferences, synthesizing the lessons established through this layered approach and facilitating their integration into breeders' product profiles.

General Correlation Between Traits, Individual, and Household Characteristics

Trait-Trait Correlation

Most of the correlations found between traits were weak (**Table 1A**). The strongest negative correlations were between fresh root yield and the quality traits: gari color, gari texture and gari taste. The strongest positive correlations were between gari texture, gari taste and gari color. Pearson correlations between traits revealed overall negative correlations between traits related to product quality (gari taste, texture, color and swelling) on the one hand with those related to yield (fresh root yield, root size, dry matter content), storability and maturity time on the other. Product quality traits positively correlated with one another; notably gari taste and texture, gari color with taste and texture, and root color with gari color. Exceptions to this were the negative and significant correlation between gari swelling and root color. Related to yield, fresh root yield positively correlated with dry matter content and maturity time, while dry matter negatively correlated with root size. Lastly, there was a weak positive correlation between disease resistance and ground storage.

Individual, Household, and Farm Characteristics

At the individual-level, there was a positive and significant correlation between female respondents and product quality trait rankings (gari taste, texture, color and swelling, root color). However, female respondents had a negative correlation with yield and agronomic traits (fresh root yield, root size and maturity time) (**Table 1B**). At the household-level, female-headed households and households with married couples showed inverse correlation results. Gari texture positively correlated with female respondents from female-headed households, but negatively correlated with female respondents that were part of a couple. Also, women in couples favored root size or disease resistance, while women in female-headed households did not. When women controlled more of the total value of activities, they favored gari color, texture and swelling more, and shorter maturity time less. This was the opposite when men controlled more of the total value of activities (**Table 1B**). These correlation results reinforce the role of gender in shaping trait preferences, and also indicate that household composition and intrahousehold dynamics further influence these rankings.

Land owned, age, crop sales, or value of crop produced did not correlate with any trait, while dietary diversity negatively correlated with root color. As a households' nutritional requirements (HHsizeMAE) increase, the less product quality traits (gari texture and color) were valued. Surprisingly, if respondents stated that they belonged to the dominant ethnicity in their community, they favored fresh root yield (**Table 1B**). The yearly production of cassava per household had several significant correlations. As production increased, prioritization of traits root yield, root size, dry matter, disease resistance and maturity time increased. However, the product quality traits of gari color, texture and taste decreased. An increase in home consumption of cassava was related to a reduction in favoring

TABLE 1A | Pearson correlations among cassava traits.

Traits	gari_ taste	gari_ texture	gari_ color	gari_ swelling	fresh_root_ yield	root_ size	dry_ matter	ground_ storage	disease_ resistance	root_ color	maturity_ time
gari_taste	1	0.277**	0.129**	−0.067	−0.294**	−0.287**	−0.092**	−0.190**	−0.192**	0.034	−0.222**
gari_texture	0.277**	1	0.247**	−0.02	−0.291**	−0.259**	−0.126**	−0.143**	−0.259**	0.017	−0.276**
gari_color	0.129**	0.247**	1	0.017	−0.300**	−0.267**	−0.165**	−0.152**	−0.252**	0.213**	−0.266**
gari_swelling	−0.067	−0.02	0.017	1	−0.170**	−0.119**	−0.151**	−0.001	−0.099**	−0.163**	−0.169**
fresh_root_yield	−0.294**	−0.291**	−0.300**	−0.170**	1	0.073*	0.246**	−0.098**	−0.086*	−0.212**	0.108**
root_size	−0.287**	−0.259**	−0.267**	−0.119**	0.073*	1	−0.121**	0.065	−0.007	−0.081*	0.059
dry_matter	−0.092**	−0.126**	−0.165**	−0.151**	0.246**	−0.121**	1	−0.230**	−0.164**	−0.144**	−0.009
ground_storage	−0.190**	−0.143**	−0.152**	−0.001	−0.098**	0.065	−0.230**	1	0.093**	−0.191**	−0.078*
disease_resistance	−0.192**	−0.259**	−0.252**	−0.099**	−0.086*	−0.007	−0.164**	0.093**	1	−0.135**	0.013
root_colour	0.034	0.017	0.213**	−0.163**	−0.212**	−0.081*	−0.144**	−0.191**	−0.135**	1	−0.077*
maturity_time	−0.222**	−0.276**	−0.266**	−0.169**	0.108**	0.059	−0.009	−0.078*	0.013	−0.077*	1

**Correlation is significant at the 0.05 level (2-tailed), **Correlation is significant at the 0.01 level (2-tailed).*

TABLE 1B | Pearson correlations between cassava traits and selected social characteristics.

Social characteristics	gari_ taste	gari_ texture	gari_ color	gari_ swelling	fresh_root_ yield	root_ size	dry_ matter	ground_ storage	disease_ resistance	root_ color	maturity_ time
Individual											
Gender	0.099**	0.083*	0.142**	0.109**	−0.072*	−0.122**	0.05	−0.079*	−0.06	0.092**	−0.145**
Age	0.04	0.018	−0.006	−0.038	−0.089*	0.029	−0.013	−0.069	0.013	0.083*	0.070*
Ethnicity	0.017	0.004	0.019	0.049	−0.094**	0.007	−0.013	0.003	0.005	0.01	−0.012
Farm											
yearly_production	0.037	0.223**	0.244**	0.141**	−0.142**	−0.187**	−0.160**	0.073	−0.159**	0.081*	−0.106**
home_consumption	−0.046	−0.069	−0.074*	0.006	0.087*	0.095**	0.006	0.06	−0.048	−0.065	0.016
LandOwned	−0.015	0.032	0.054	−0.059	−0.022	−0.008	0.033	−0.034	−0.006	0.056	0.009
farmsize_acre	0.073	0.138**	0.181**	0.074	−0.015	−0.082	−0.051	0.085	−0.127*	−0.009	−0.091
CropDiv	0.044	−0.124**	−0.075*	−0.075*	0.056	0.004	0.086*	−0.183**	0.059	0.063	0.110**
Cropsales	−0.006	−0.011	−0.053	−0.001	−0.005	0.035	−0.041	0.068	0.035	0.025	0.011
Valuecropproduce	−0.006	−0.009	−0.052	0	−0.004	0.033	−0.039	0.067	0.033	0.025	0.01
House hold											
HHsizeMAE	0.004	0.094**	0.131**	0.048	−0.043	−0.034	−0.009	−0.038	−0.056	0.051	−0.085*
HDDS	0.051	0.052	0.092*	−0.066	−0.036	−0.048	−0.004	0.004	−0.051	0.113**	0.009
HFIAS	−0.037	−0.130**	−0.097**	−0.056	0.057	0.095**	0.077*	−0.058	0.077*	−0.023	0.061
FoodInsecure_yn	−0.051	−0.088*	−0.075*	−0.086*	0.052	0.107**	0.075*	−0.038	0.059	−0.047	0.06
PPI_Likelihood	0.034	0.104**	0.056	0.06	−0.005	−0.028	0.021	−0.093**	−0.004	−0.081*	−0.107**
PPI_Below10	−0.047	−0.079*	−0.025	−0.011	0.034	0.012	0.049	0.057	−0.012	0.038	0.012
PPI_10to30	0.036	0.034	−0.006	−0.032	−0.053	−0.008	−0.082*	−0.005	0.022	0.022	0.063
PPI_over30	0.025	0.088*	0.056	0.075*	0.028	−0.008	0.048	−0.097**	−0.015	−0.106**	−0.128**
Gender_MaleControl	0.029	0.079*	0.130**	0.081*	0.013	−0.056	−0.042	0.02	−0.035	−0.045	−0.134**
Gender_FemaleControl	−0.045	−0.095*	−0.122**	−0.085*	−0.007	0.07	0.046	−0.041	0.03	0.049	0.147**

*Correlation is significant at the 0.05 level (2-tailed), **Correlation is significant at the 0.01 level (2-tailed).*

root size, while as the farm size increased, product quality traits gari texture and color was less favorable. In general, household and farm characteristics that related to larger production and market-orientation correlated to output-related trait preferences.

As household food insecurity increased (HFIAS), there was an increased interest in product quality traits (gari texture and color) and a decreased interest in root size. As households had higher probability of being in poverty (higher PPI index), respondents favored product quality traits (gari texture) less, while favoring ground storage and short maturity time more. This pattern was mirrored when the indicator was separated into poverty categories (<PPI 10% being "non-poor"), with the "poor" category (PPI above 30%) (**Table 1B**).

Gender, Poverty, Region, and Food Security as Drivers of Trait Ranking

To explore relationships between trait prioritization and selected variables of interest, we focused on gender, region, food security and poverty using Odds Ratio estimates. Building from the exploratory analysis of correlations, this reduces the potential of interpreting possible spurious correlations to allow for more explicit comparisons between potential market segments.

Gender

Women tend to prioritize food product quality traits and root color more, while men tend toward root size and maturity time, as well as ground storage and disease resistance. The traits prioritized by women show larger differences between men and women than other traits, with gari color showing the largest difference (**Tables 2**, **3**). Women are more likely to prioritize root color (men are 35% more likely to rank it low), gari taste (51%), texture (31%), color (59%) and swelling (44%) than men. Men, on the other hand, are less likely to lowly rank root size (men are 35% less likely to rank it low), in ground storability (28%), disease resistance (26%) and maturity time (41%), with maturity time showing the largest difference (**Table 3**). For dry matter content and fresh root yield there is no difference between men and women.

Household Food Insecurity Index

Analysis of the HFIAS categories revealed 265 (34%) people as severely food insecure, 352 (45%) people as moderately food insecure, 63 (8%) people in mild food insecure and 105 (13%) people in food secure. In simplifying this to only compare between food secure and food insecure households, we see distinct differences in their likelihood to prefer some traits over others. Food insecure households are less likely to rank gari texture low (33%) but are more likely to give a low rank to root size (57%) and dry matter content (41%) (**Table 3**).

TABLE 2 | Odds ratio estimates for the differences between women and men, Food Secure vs. Food Insecure and Non-poor vs. Poor, and between the different regions for each of the 11 traits.

Category	Reference	Gari taste	Gari texture	Gari color	Gari swelling	Fresh root yield	Root size	Dry matter	In ground storage	Disease resistance	Root color	Maturity time
Men	Women	1.428**	1.319*	1.667***	1.484**	0.768*	0.649***	1.193*ns*	0.75*	0.771*	1.381*	0.598***
Food insecure	Food secure	0.781*ns*	0.668*	0.770*ns*	0.765*ns*	1.396*ns*	1.574**	1.410*	0.782*ns*	1.19*ns*	0.802*ns*	1.260*ns*
Non-poor	Poor	1.216*ns*	1.428**	1.147*ns*	1.047*ns*	0.855*ns*	0.931*ns*	0.828*ns*	0.779*ns*	0.994*ns*	0.873*ns*	0.932*ns*
North Central	South West	1.018*ns*	0.839*ns*	*ns*	1.170*ns*	0.958*ns*	0.667***	1.029*ns*	1.207***	1.538*ns*	0.615***	0.777***
South East	South West	1.073*ns*	0.475***	0.560***	0.577***	1.010*ns*	1.256**	1.559***	0.504***	1.618*ns*	1.199*ns*	2.477***
South South	South West	0.559***	0.600*ns*	1.499***	1.261**	0.480***	1.015*ns*	0.904*ns*	0.846*ns*	2.253***	1.872***	1.454*ns*
South East	South South	1.919*ns*	0.792***	0.374***	0.457***	2.103*ns*	1.237*	1.725***	0.595***	0.718*ns*	0.641*ns*	1.704***
North Central	South East	0.948*ns*	1.766*ns*	1.863*ns*	2.028*ns*	0.949*ns*	0.531***	0.660*ns*	2.395***	0.951*ns*	0.513***	0.314***
South South	North Central	0.549***	0.715*ns*	1.437***	1.078*	0.501***	1.522*ns*	0.878*ns*	0.701*ns*	1.465***	3.043***	1.871*ns*

*Indicate p-value < 0.05, **p-value < 0.01, and ***p-value < 0.001 levels of significance respectively.*

TABLE 3 | More (+) or less (–) odds (%) of ranking a trait low comparing the social binary categories of men/women, Food Insecure/Food Secure and Non-poor/Poor [based on the Poverty Probability Index (PPI) and Household Food Insecurity Access Scale (HFIAS)].

Trait	Men (comp. to Women)	Food insecure (comp. to Food Secure)	Non-poor (comp. to Poor)	SE (comp. to SW)	NC (comp. to SW)	SS (comp. to SW)	SE (comp. SS)	NC (comp. to SE)	SS (comp. to NC)
Gari taste	51					−44			−45
Gari texture	31	−33	43	−52			−21		
Gari color	59			−44		55	−63		44
Gari swelling	44			−42			−54		8
Fresh root yield						−52			−50
Root size	−35	57		25	−33		24	−47	
Dry matter		41		56			73		
In ground storage	−28			−49	21		−41	140	
Disease resistance	−26					125			47
Root color	35			148	−35	87		−49	204
Maturity time	−41				−28		70	−69	

*Odds values are based on calculated odds ratios (**Table 2**).*

Poverty Probability Index

In analyzing the PPI index, 575 people fell below a PPI index of 10% and were classified as non-poor, while 217 people were above a PPI index of 10% and classified as poor. Gari texture is the only trait significantly different between households that were classified as poor, and those that were not (**Table 2**): non-poor households are 43% more likely to rank gari texture low than households that were classified as poor (**Table 3**).

Regional Differences

Building from previous analysis, we find distinct regional variation in the prioritization of product quality traits (**Table 2**). Overall, gari texture, gari color and gari swelling were less likely to be ranked low (less odds in ranking the trait low) in the South East, compared to the South South and South West. Gari taste was less likely to be ranked low in the South South, compared to the South West and North Central. Lastly, gari color was more likely to be ranked low in the South South compared to the North Central and South West (**Table 3**).

There were regional variations in the prioritization of agronomic traits (**Table 2**). The highest differences were observed for root color, disease resistance and in ground storage. Root color was 148% more likely to be ranked low in the South East and 87% more likely to be ranked low in the South South when compared to the South West. The same trait was 204% more likely to be ranked low in the South South when compared to the North Central. In the North Central root color was less likely to be ranked low compared to other regions. Disease resistance was 125% and 47% more likely to be ranked low in the South South when compared to the South West and North Central respectively. Inground storage was 21% and 140% more likely to be ranked low in the North Central when compared to the South West and South East respectively, while the same trait was less likely to be ranked low in the South East. Maturity time was less likely to be ranked low in North Central when compared to the South West and South East, while the same trait was 70% more likely to be ranked low in the South East compared to the South South. Fresh root yield was about 50% less likely to be ranked low in the South South when compared to the South West and North Central. Root size was less likely to be ranked low in the North Central when compared to the South West and South East, but more likely to be ranked low in the South East when compared to the South West and South South. Lastly dry matter was more likely to be ranked low in the South East when compared to the South West and South South (**Table 3**).

Social Categories' Interaction With Gender

Social differences are not experienced homogenously. Therefore, it is critical to not just compare across these categories, but also understand the complexities within them. To move beyond previous analysis, we use a Wilcoxon test to investigate the interaction of gender with each of the following categories: food insecurity, poverty, and region (**Table 4**). We find that, in comparing the average trait ranking among food insecure households, women prioritize gari-related traits and root color more than men, while men prioritize agronomic traits more. This pattern was not observed for food secure respondents, where the only differences found between men and women were in the rankings of gari taste and maturity time. There was much less difference between women and men from non-poor households than between women and men from poor households. Among non-poor households only gari swelling was more prioritized by women, and men prioritize fresh yield and root size was more than women.

There are very clear interactions of sex with region. In the South West, women prioritize gari-food product quality traits and root color more than men do. Consistently, men prioritize agronomic characteristics more than women. However, there is no difference in prioritization between men and women for gari swelling and in ground storability. For the North Central, there are only three traits that differ in average ranking for men and women: gari swelling is ranked higher by women, while fresh yield and root size are ranked higher by men. For the South East and South South only fresh yield is ranked higher by women than men, and men prioritize in ground storability more in the SS.

Summative Heatmap

Figure 2 shows the interactions between gender and all the other social variables using a trait ranking heatmap as a broad-brush summary of results. From this visual, we observe that food insecure non-poor women in the South South give very low priority to disease resistance but very high priority to fresh root yield. Women from non-poor food secure households in the South West give very low priority to root color, while

TABLE 4 | Wilcoxon test for independent samples comparing gender differences for trait prioritization within food security, poverty and regional differences.

Social/regional category		*N*	Gari taste	Gari texture	gari color	Gari swelling	Fresh yield	Root size	Dry matter	In ground storage	Disease resistance	Root color	Maturity time
Food secure	*P*-value		**0.023**	0.788	0.058	0.539	0.766	0.317	0.142	0.671	0.643	0.090	**0.016**
	Median women	54	7	9	5.5	7	3	6	5	6	7.5	8.5	7
	Median men	58	9	9	7	8	4	5	6	5.5	7	7	6
Food insecure	P-value		0.053	**0.041**	**0.001**	**0.003**	**0.032**	**0.003**	0.259	**0.016**	**0.016**	**0.001**	**0.002**
	Median women	428	6	7	5	6	5	7	6	5	9	7	8
	Median men	252	7	8	7	7	4	6	6	4	8	8	7
Poor	P-value		**0.008**	**0.008**	**0.000**	**0.013**	0.067	**0.011**	0.291	**0.008**	0.248	**0.046**	**0.000**
	Median women	341	6	7	5	6	5	7	6	5	9	7	8
	Median men	234	7	7.5	7	8	4	6	6	4.5	8	8	6.5
Non-poor	P-value		0.297	0.900	0.250	0.060	0.267	**0.020**	0.370	0.852	**0.0350**	0.139	0.067
	Median women	141	6	8	6	7	4	7	6	4	9	7	8
	Median men	76	8	8	6	8	4	6	6	4	7	8	6.5
North Central	P-value		0.081	0.753	0.057	**0.031**	**0.011**	**0.030**	0.517	0.356	0.998	0.058	0.185
	Median women	123	7	8	6	7	5	6	6	7	9	5	6
	Median men	76	8	8	6	9	4	5	6	5	9	6	6
South East	P-value		0.111	0.787	0.914	0.065	0.301	0.431	0.557	0.472	0.738	0.187	0.062
	Median women	104	8	6	4	5	5	8	7	4	9	7	10
	Median men	93	6	6	4	6	5	7	7	3	8	8	8
South South	P-value		0.156	0.735	0.387	0.711	**0.046**	0.485	0.537	**0.027**	0.158	0.247	0.359
	Median women	133	5	6.5	7	8	2	7	5	5	10.5	9	7
	Median men	69	6	7	7	8	4	7	6	4	9	8	7
South West	P-value		**0.000**	**0.001**	**0.000**	0.149	**0.000**	**0.003**	0.093	0.157	**0.000**	**0.011**	**0.000**
	Median women	122	5	7	5	7	6	8	5	6	8	7	8
	Median men	72	9	9	8	7.5	4	5	6.5	5	5	8	5

Values are ranks, so a lower number means a higher rank.
P < 0.05 are in bold.

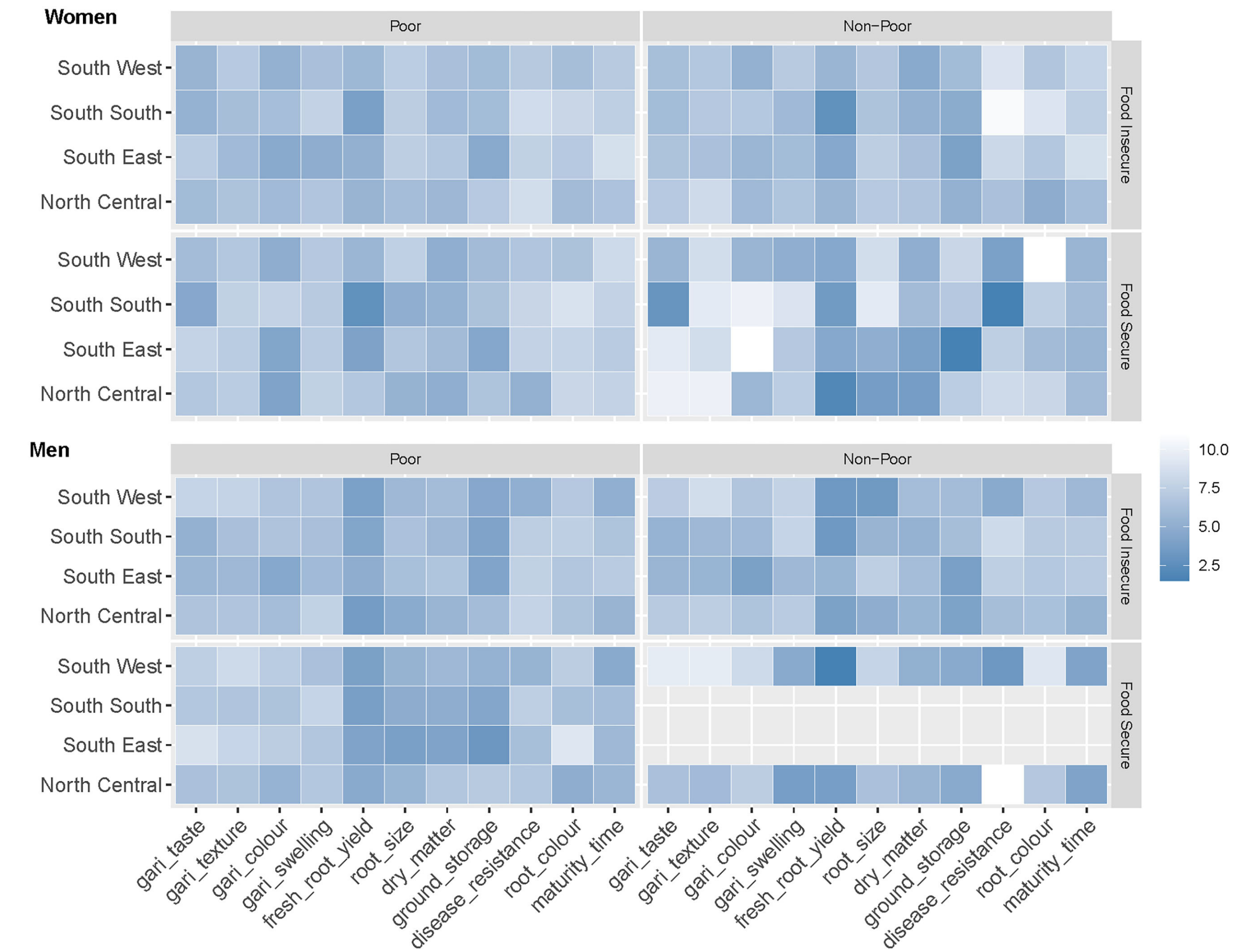

FIGURE 2 | Heatmap of interactions between gender and social variables and household characteristics for level of trait prioritization (rank of 11 traits). A lower number represents a higher average rank and thus priority. There were no male respondents from the SS and SE that were classified as food secure and non-poor.

women from non-poor food secure households in the South East give very low priority to gari color. Furthermore, food secure non-poor women from the South South give a very high priority to disease resistance while women in this category from the South East give a very high priority to in ground storability. There were no food secure non-poor men in the South South and South East represented among the respondents. Food secure non poor men in the North Central gave very low priority to disease resistance while food secure poor men in the South West give very high priority to fresh root yield.

DISCUSSION

This study sought to broaden the narrative around trait preference studies, to move beyond oversimplification and comparison of men and women by providing richer analysis of end users of cassava varieties. The intention is to more accurately analyze the data guiding breeders' understanding of smallholder cassava farmers in Nigeria, and their preferences, to develop more informed product profiles. Teeken et al. (2018) outlines the importance of applying a gender lens to understanding trait and varietal preferences, finding differences in trait preferences between women and men across South East and South West. This study expands this approach, with a larger set of respondents, new approaches and tools for deeper analyses.

Gender Continues to Matter

This study found significant differences in prioritization between women and men of differential cassava trait preferences in Nigeria. This confirms both earlier primary studies on trait preferences (Bentley et al., 2017; Wossen et al., 2017; Teeken et al., 2018), as well as reports outlining differential gender roles along the cassava value chain and women's high involvement in cassava processing and marketing (Curran et al., 2009; Walker et al., 2014). Balogun et al. (2021) also showed that women are more likely to prefer quality traits. Our results follow these earlier findings that women prefer product quality traits, while men prefer productivity-related traits. This confirms the opportunity for breeding programs to prioritize product quality traits, especially gari color, taste, texture and swelling. There is need to develop high throughput phenotyping approaches, experimental designs, and extensive genetic studies to reflect the importance of these traits. Doing so would reflect the value breeding programs place on gender equality goals.

Interestingly this broad bifurcation of trait preferences, women favoring product quality traits and men favoring productivity related ones, was reflected even when looking at household types and value of household activities. Households headed by single women reflected a preference of quality traits, while preferences shifted toward productivity traits for couples in households. Chiwona-Karltun et al. (1998) also found unique preferences for female-headed households, which reflected their social vulnerability. This study observed a similar preference pattern when control of value of household activities was higher for women or men. Together these results support the argument that gender analysis should be central to breeding priority setting because preferences remain strongly correlated with sex of the respondent, the role of women within households, and their control of resources.

Regional Differences Are Complex but Draw Lessons Important for Breeding

Product quality is of utmost importance in South East Nigeria. There is a cultural context shaping the relationship between cassava and its food products in this region, where harvests and processing are regulated to specific days, and farmers seek to add as much value as possible to the cassava that is harvested from small plots (Teeken et al., 2018). Furthermore, as the Pearson correlation between the traits has shown, quality traits become more important when more of the roots are used for home consumption. That root color is far more important in the South West and North Central than in other regions can relate to the longer fermentation practiced in these regions, which can cause discoloration of the roots. In the other regions, gari is colored using red palm oil (Awoyale et al., 2021; Chijioke et al., 2021; Teeken et al., 2021). Teeken et al. (2021) found that a variety disliked because of discoloration in the South West (where there is long fermentation) was not clearly disliked in the South East. Some of the regional differences in variation in gar fermentation may also reflect product quality trait differences (Ndjouenkeu et al., 2021).

It is also remarkable that in-ground storage is not prioritized in the North Central region. This could relate to more commercially oriented cassava farming in this region, where there is also an existing seed system (Bentley et al., 2020). In this case, harvesting more roots at the same time for the market is more important than the need for storability. In the South East, there is a concentration of poorer female farmers (Orr et al., 2018), where farming on small plots for home consumption and relatively small local markets. This may necessitate more in-ground storability (to facilitate piece-meal harvesting) compared to other regions. Prioritization of root size and maturity time in North Central may equally be explained by the more commercially organized markets demanding for marketable larger roots. We observed that root size in the South East is less important than in the South West where there are market connections to other states and cities (Abdoulaye et al., 2013).

The South South was unique in the high priority on gari taste and fresh root yield but low priority given to gari color and root color. One explanation can be that gari and eba are relatively less important in the diet of people in the South South where fufu is more important, but cassava is also consumed in starch dough form (Etejere and Bhat, 1985). Furthermore, most gari is colored yellow by adding palm oil which makes the shininess more important than the actual color (Ndjouenkeu et al., 2021). The importance placed on fresh root yield here could be explained by the land scarcity and relatively small plot sizes in the South East and South South when compared to other regions (Korieh, 2010; Teeken et al., 2018). It can also be explained by the predominance of landraces in the South South (Pircher et al., 2019) that are good for food product quality so the quality is already assumed good in any future variety improvement scenario. Counter to the observed gender trait differences, women in South South and South East prioritize fresh root yield. This can be understood by the major role women have within agriculture in these regions where men are more involved in other businesses and rely on the expertise of women with regards to farming and/or are fully involved in similar practices when cassava farming and processing is concerned (Enete et al., 2002).

These observations suggest a clear regional difference in trait preferences that can be related to the relative importance of different food products (Dufour et al., 2021). Specific regional (food) cultural factors (Ntumngia, 2012) should be considered when developing variety replacement strategies. Such differences should be considered to make a new variety more competitive or have strong complementarity (Mbwentchou Yao, 2021) to the most popular varieties in the region. In-ground storability seems crucial for smaller scale farmers that live under less secure circumstances requiring flexibility, while early maturing high yielding varieties with lower in-ground storage ability complement better to the variety portfolio of larger farmers that can afford a more fixed farming schedule.

Considering Poverty and Food Security Could Help Develop More Impactful Breeding Products

We found a strong correlation between food insecurity and difference in cassava trait preferences between men and women. As households become more food insecure, the differences in prioritization between men and women increases. This could be because cassava occupies a greater part of the diet and income generation within food insecure households. Gegios et al. (2010) show a negative relation between nutritional status of children and high consumption profile of cassava. The quality and market price of the product and its eating experience might therefore become relatively more prevalent. Similar tendency is true when considering Poverty Probability where gender differences appear among households that are poor. This could indicate that within non-poor households' the division of labor is less pronounced making men and women, prioritize traits more similarly (Alawode et al., 2017). This also highlights the overall importance of gari swelling for women and yield for men as these traits cut across food insecure and poor households.

Combining insights from different social identities and household characteristics, it is clear that gari texture is the most crosscutting trait in terms of its importance. Gari texture highly influences gari quality and market price. This confirms findings of Ezedinma and Nkang (2008) that good texture/taste is a major reason that influences willingness to pay for gari, Considering food security however added nuance to this assumption: Women in food insecure and poor households value texture more, while gari texture is the only trait that is generally (men and women combined) also valued more by food insecure households and poor households (**Table 3**).

Food security, region, and poverty level all interact with gender in defining trait preferences, reflecting the importance of looking at heterogeneity among social groups especially in defining breeding priorities. This research has identified quality traits and food security traits like in ground storability as essential if breeding programs intended to positively impact poor and food insecure households. These results reinforce the importance of recognizing social difference and the heterogeneity among men and women. Individual and household characteristics interact to reveal traits that are highly variable across differences. This information can inform trait prioritization for product profiles, labelling traits that are cross-cutting in importance as "non-negotiable." Furthermore, the demonstrated grouping of traits per region would be highly informative for breeding programs to consider regionally focused breeding pipelines. Together, this study has potential to guide development of breeding products that have higher social impact, which may ultimately serve the more vulnerable and align with development goals. Deeper understandings of social dimensions provide insights into the true experience of farmers in order to develop product profiles that support the public and breeding programs' development and social impact objectives.

DATA AVAILABILITY STATEMENT

The datasets related to this this study can be found in the CKAN http://data.iita.org repository of IITA: Teeken, B., Garner, E., Afolabi, A., Balogun, I., Olaosebikan, O., Bello, A., Madu, T., Okoye, B., Egesi, C., Kulakow, P., & Tufan, H. A. (2021). Beyond "women's traits": Exploring how gender, social difference and household characteristics influence trait preferences [Data set]. International Institute of Tropical Agriculture (IITA). https://doi.org/10.25502/RHJ9-2228/D.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by internal review board of the International Institute of Tropical Agriculture. IITA has the mandate to carry out research in Nigeria including human subjects based on an agreement with the Nigerian government. The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

HT conceived the original manuscript idea and wrote the manuscript. BT and EG analyzed the data and wrote the manuscript. AA and IB analyzed the data. OO, AB, TM, and BO contributed to fieldwork and reviewed the manuscript. CE and PK reviewed the manuscript. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

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What Farm Size Sustains a Living? Exploring Future Options to Attain a Living Income From Smallholder Farming in the East African Highlands

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Smallholder farming in sub-Saharan Africa keeps many rural households trapped in a cycle of poor productivity and low incomes. Two options to reach a decent income include intensification of production and expansion of farm areas per household. In this study, we explore what is a "viable farm size," i.e., the farm area that is required to attain a "living income," which sustains a nutritious diet, housing, education and health care. We used survey data from three contrasting sites in the East African highlands—Nyando (Kenya), Rakai (Uganda), and Lushoto (Tanzania) to explore viable farm sizes in six scenarios. Starting from the baseline cropping system, we built scenarios by incrementally including intensified and re-configured cropping systems, income from livestock and off-farm sources. In the most conservative scenario (baseline cropping patterns and yields, minus basic input costs), viable farm areas were 3.6, 2.4, and 2.1 ha, for Nyando, Rakai, and Lushoto, respectively—whereas current median farm areas were just 0.8, 1.8, and 0.8 ha. Given the skewed distribution of current farm areas, only few of the households in the study sites (0, 27, and 4% for Nyando, Rakai, and Lushoto, respectively) were able to attain a living income. Raising baseline yields to 50% of the water-limited yields strongly reduced the land area needed to achieve a viable farm size, and thereby enabled 92% of the households in Rakai and 70% of the households in Lushoto to attain a living income on their existing farm areas. By contrast, intensification of crop production alone was insufficient in Nyando, although including income from livestock enabled the majority of households (73%) to attain a living income with current farm areas. These scenarios show that increasing farm area and/or intensifying production is required for smallholder farmers to attain a living income from farming. Obviously such changes would require considerable capital and labor investment, as well as land reform and alternative off-farm employment options for those who exit farming.

Keywords: household income, income distribution, livelihood strategies, scenario exploration, future farming systems, intensification, poverty

INTRODUCTION

It has been estimated that of the world's poor, almost two thirds work in agriculture (Olinto et al., 2013). In sub-Saharan Africa (SSA), smallholder farming can be a vicious cycle of low productivity and limited re-investment, keeping farming households trapped in poverty (Tittonell and Giller, 2013). The massive engagement in agriculture is a symptom of lack of access to alternative livelihood sources, with farming often being a last resort (Koning, 2017; Giller et al., 2021). Farming is not the primary interest for youth, who have other aspirations for employment. However, agriculture remains an important option, though often as a fall-back (e.g., Ramisch, 2014; LaRue et al., 2021; Sumberg et al., 2021).

Dorward et al. (2009) differentiate trajectories of farming households that are "stepping up" from those who are "stepping out" or simply "hanging in." Households with sufficient resources to invest can "step up" toward more lucrative farming, whereas some choose to "step out" of farming when job opportunities arise in other sectors such as industry (Dorward et al., 2009). For some agriculture generates so little that they can only "hang in." The pressure to step up or out of farming increases, because cultivated areas per farm are decreasing—and more so for those who already have the smallest cultivated areas (Headey and Jayne, 2014; Jayne et al., 2014; Giller et al., 2021).

With ever smaller farms, it becomes increasingly urgent to intensify production or to pursue alternative livelihood strategies. Simultaneously there is a growing demand for food from the burgeoning population in SSA, requiring intensification of farming to achieve self-sufficiency at national level (van Ittersum et al., 2016). Yet even when production is intensified, farms can simply be too small to obtain a decent living (Harris and Orr, 2014; Giller et al., 2021). This creates the imperative to investigate how smallholder incomes can be increased, given their small farm sizes, while at national level, increases in agricultural production are required to achieve food self-sufficiency (Giller, 2020). In pursuit of Sustainable Development Goals (SDGs; United Nations, 2015)—and SDG 1 Zero Poverty and SDG2 No Hunger, in particular—it is important to understand whether and how farming can be(come) a viable livelihood strategy, especially for the smallest farms. Whether through subsidies to increase yields, through land reform to increase farm sizes or other measures (Koning, 2017), the protection and support of the smallest farms needs to be considered to "leave no one behind" in the SDGs.

Many studies have shown that current, small farm sizes limit the incomes of smallholder farmers (e.g., Frelat et al., 2016; Marinus, 2021). Others have calculated what farm area would be required to reach the poverty line in dryland farming systems in SSA and India (Harris and Orr, 2014; Gassner et al., 2019). So far however, no studies have determined the minimum farm area required for households to reach the living income benchmark. Moreover, earlier assessments considered current cropping practices without exploring the effects of growing more profitable crops such as vegetables. In this study we use "living income" as a benchmark for the viability of farming (Anker and Anker, 2017b; van de Ven et al., 2020). The living income concept has recently gained attention (Living Income Community of Practice, 2021). It estimates the income that is required for a decent living (Anker, 2011; van de Ven et al., 2020), on the basis of the principles in the universal declaration of human rights (United Nations General Assembly, 1948). It therefore includes the income needed to provide a nutritious diet, housing, education and health care (Anker, 2011; van de Ven et al., 2020). The commonly used poverty line benchmark considers the minimum cost of living in the poorest countries in the world (Ravallion et al., 1991; Chen and Ravallion, 2010). As such, the living income is an addition to the commonly used poverty line benchmark (van de Ven et al., 2020).

The overall goal of this paper is to explore what farm area would be required to attain a living income from farming which we refer to as the "viable farm size." We first assessed how current smallholder incomes (reported in survey data) compared with the site-specific living income thresholds, and investigated the contributions from crops, livestock and off-farm income. We then estimated viable farm sizes for several scenarios: first on the basis of current yields and crop area allocation, then on the basis of possible future intensification (increased yields) and then in addition, with more profitable crop configurations. Moreover, we examined contributions from livestock and off-farm income and how they affect the viable farm size. Lastly, we compared current farm sizes with viable farm sizes. Our analysis is focused on three contrasting sites in the East African highlands: Nyando in Kenya, Rakai in Uganda, and Lushoto in Tanzania.

Our research was guided by the following research questions:

1. What percentage of the farming population currently achieves a living income?
2. What farm size can provide a living income with current cropping systems—i.e., what is a viable farm size?
3. What are the implications of (a) intensification of the cropping system and (b) considering other sources of income, on the viable farm size?

METHODOLOGY

Three Contrasting Sites

Survey data was used from three contrasting sites in East Africa: Nyando in Kenya (2016), Rakai in Uganda (2017), and Lushoto in Tanzania (2015) (**Table 1**). All three sites have rainfall patterns that allow two cropping seasons each year. Nyando is located in the mid-lands of western Kenya, on the slopes next to Lake Victoria. Small streams and rivers cross the area from the upland areas toward the lake. As these river valleys often flood, they are commonly used for grazing livestock, while crops are cultivated on the elevated areas. Crops and livestock are both important for household income. Common crops are maize, beans, and sorghum (Mango et al., 2011; Kung'u and Namirembe, 2012). In Nyando, the relative importance of livestock is much larger than in Rakai and Lushoto. Rakai is located in the southern part of central Uganda and is characterized by an undulating landscape. It has a diverse cropping system, distinguishing itself from the other two sites by the importance of perennial crops, i.e., coffee and East African highland banana (referred to as

TABLE 1 | Characteristics of the three research sites in the East African highlands from the RHoMIS database (van Wijk et al., 2020).

	Nyando (Kenya)	Rakai (Uganda)	Lushoto (Tanzania)
Sample size (no. households)	155	113	120
Household size (adult equivalents)	4.0	4.4	3.3
Population density (people km^{-2})[a]	214	190	310
Total rainfall (mm year^{-1})[b]	1,618	1,208	1,148
Rainfall seasonality classification[c]	Humid (year round)	Single wet season regime, bimodal	Single wet season regime, uni-bimodal
Farming systems (crops)	Main crops: maize, beans, sorghum, sugarcane	Coffee-banana intercropping with many other crops including: beans, maize, cassava	Main crops: Maize, beans, Irish potato and vegetables (cabbage, tomato) in the valleys

[a]*CIESIN (2018); NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.~7927/H49C6VHW.*
[b]*CHIRPS Rainfall Data: 2010–2019 yearly average (Funk et al., 2015).*
[c]*Continental classification of rainfall seasonality regimes in Africa (Herrmann and Mohr, 2011).*

banana hereafter). Other important crops are beans, maize and cassava (Kyazze and Kristjanson, 2011). Lushoto is located in the west Usambara mountains in northern Tanzania and has an undulating, hilly landscape. Valley bottoms are commonly used to grow vegetables such as cabbage and tomato, which are transported for sale in urban markets in Tanga and Dar es Salaam. Other important crops are maize, beans and Irish potato (Lyamchai et al., 2011). Population densities in the three sites (**Table 1**) are typical for the areas where the largest part of the population of the East African highlands lives (Vanlauwe et al., 2013).

Estimating Current Value of Crops and Household Income

The Rural Household Multi-Indicator Survey (RHoMIS; Hammond et al., 2017) formed the primary data source and data were obtained from van Wijk et al. (2020). RHoMIS offers a relatively rapid and largely standardized questionnaire, aimed at estimating the well-being of farming households. The RHoMIS survey adheres to the principles of the 1964 WMA declaration of Helsinki (van Wijk et al., 2020). The survey was executed in 2016 in Nyando (155 households), in 2017 in Rakai (113 households), and in 2015 in Lushoto (120 households) (**Table 1**). From this household-level dataset, we extracted variables on household composition, total area cultivated, production metrics and economic value received (step 1a and 1b in **Figure 1**). Production in the previous year was reported for each type of crop grown and livestock owned, as well as the fractions consumed and sold, and the total income received for the sold amount. From these variables we derived the price per crop and livestock product per household. Following the RHoMIS approach (Hammond et al., 2017), prices were triangulated with prices from literature and where needed replaced by prices from literature. This was in particular the case for crops for which it is difficult to derive prices per kg, e.g., banana which is sold per bunch and when reported prices deviated a lot from literature (**Supplementary Material 1**). We then calculated the total value of crop and livestock produce per household, at the median price per site of each product. All prices of products were standardized to 2017 (year of the latest survey and converted to USD purchasing power parity (USD PPP) to enable comparison among sites. Income from off-farm sources was reported as the proportion of total income at household level, so we derived its value from the total value of sold farm produce (Hammond et al., 2017). We refer to "value of produce" when considering the value of crops and/or livestock produced on the farm and refer to "income" when all sources of household income are considered: i.e., value of crop produce, value of livestock produce and off-farm income. Income per household was expressed per Adult Equivalent (AE) following (OECD, 2011), using the household composition from the survey.

Living income estimates were used from Anker and Anker (2017a) for Kenya and from van de Ven et al. (2020) for Tanzania and Uganda. Living income estimates were all standardized to 2017 (van de Ven et al., 2020). The living income includes costs for a low-cost nutritious diet, housing, education, health care and unforeseen costs and is based on an average household composition and size (see van de Ven et al., 2020). The extreme poverty line benchmark of USD PPP 1.90 was assumed to be per adult equivalent and was corrected for inflation up till 2017, so that the extreme poverty line benchmark was set at USD PPP 2.08 per adult equivalent per day in all three study sites.

Preparing Baseline Data for Scenario Exploration

For the exploration of viable farm sizes in current and intensified cropping systems, we first established what was a representative, baseline cropping system per site. The RHoMIS data provided information on production per farm and per year and was not designed to capture crop yields or intercropping, and information on seasonal crop area allocation was only available for Rakai. In each of the study sites, intercropping is a common practice, and the bimodal rainfall pattern enabled that some crops are cultivated in one or in both cropping seasons. Because of this, crop yields could not be derived adequately from the survey, and resulted in unrealistically low estimates (**Supplementary Material 2**). Therefore, baseline yields were derived from literature instead of the survey (**Supplementary Material 2**). Seasonal crop cultivation patterns (which crop is cultivated in which season) were also based on literature for Nyando and Lushoto (MoALF, 2016; Marinus, 2021), while season-specific data was available for this from the survey in Rakai. For each of the sites, we assumed that maize was

1. Estimating current value of crops and total household income

1a. RHoMIS survey data

Variables reported in RHoMIS:
- Household size (number per age category)
- Cultivated area
- Crops grown

- Crop production (kg year^{-1} [Nyando&Lushoto]; kg season^{-1} [Rakai])
- Crop proportion sold / consumed / fed to livestock
- Value received for sold produce
- Crop area proportion (RHOMIS defines none = 0, little = 0.1, under half=0.2, half = 0.5, most = 0.7, all = 0.9)

- Livestock owned
- Value received for sold livestock (products)

- Proportion of income that is from off-farm sources

1b. Data processing

Variables derived from RHoMIS, all per household:
- Household size (adult equivalents)
- Cultivated area (ha)
- Number of people growing each crop

- Crop area proportion (re-scaled to sum to 1)
- Crop price (USD PPP kg^{-1})

>> *We set all prices at median value per crop type*
>> *Prices were triangulated with literature*
- Total value of crops (USD PPP year^{-1}, sold + consumed)

- TLU
- Total value of livestock products (USD PPP TLU^{-1} year^{-1}, sold + consumed)

>> *We set all prices at median value per livestock type*

- Total off-farm income (USD PPP year^{-1})

2. Preparing baseline data for scenario explorations

2a. Triangulation of crop values

Information that was not available in the RHOMIS survey was derived from literature:
- Crops grown: now specified separately for the short and long cropping seasons in all sites (literature)
- Maize and beans assumed to be intercropped in all sites (literature)
- Crop yields: season-specific values (literature)

2b. Simplification

>> *We set household size to the median per site*

We focus on main crops per season only, per site:
- Crops with (median area proportion * proportion of the population growing the crop) > 5%, per season
- Other crops & crop areas are excluded from the analysis
- Area proportions of main crops are re-scaled to sum to 1 (bean area is equated to that of maize, and not summed)

3. Incremental scenarios to estimate the viable farm size

B1: baseline yields
- Crops only, at baseline yields

\+ **B2: baseline yields - costs**
- Requirements of fertilizer for main crops was estimated based on the 'soil supply yield' (literature, experts)
- Costs of seed and fertilizer were subtracted from the value of crop produce (literature)

\+ **I1: improved yields**
- Baseline yields were replaced with 50% of the water-limited yields (literature)
- Input costs were updated to match higher yields

\+ **I2: profitable crops**
- Crop areas were re-allocated so that 20% of the cultivated area is used for the main vegetable
- Area proportions of other main crops were re-scaled to sum to 1

\+ **O1: livestock income**
- An additional source of income was included: the value of livestock. This value was the median number of TLU times the median value of a TLU (RHOMIS)

\+ **O2: off-farm income**
- An additional source of income was included: off-farm work. This value was the median off-farm income (RHOMIS)

FIGURE 1 | A schematic overview of the scenarios and progression of variables and values with every step in the methodology. TLU, tropical livestock unit; PPP, purchasing power parity (2017).

intercropped with common bean, whenever maize was cultivated. The survey-reported crop area proportions did not always add up to one (**Supplementary Material 3**), and were therefore rescaled proportionally to add up to one for each farm, for the main cropping season in each site. It was then assumed that if a crop was grown also in the minor season (based on literature), it was allocated the same area. We determined what were the main crops per site, by weighting the median proportion of farm area allocated to a crop by the proportion of the population growing it. In our simulated baseline cropping systems, we included only the main crops per site: i.e., those with a weighted area proportion equal to or larger than 5%. The weighted area proportions were then proportionally scaled to add up to one.

Scenarios Exploring the Viable Farm Sizes

Viable farm sizes were assessed for six incremental scenarios (**Figure 1**). The *baseline*-scenarios (*B1: baseline yields* and *B2: baseline yield - costs*) were used to explore the viable farm size within the baseline cropping system. The *crop intensification*-scenarios (*I1: improved yields* and *I2: profitable crops*) were used to explore how possible future options for intensification—increasing yields and cultivating more profitable crops—would change the viable farm size. The *other income sources*-scenarios (*O1: livestock income* and *O2: off-farm income*) assessed the impact of incorporating current income from sources other than crops, namely livestock and off-farm income sources.

Baseline crop yields, crop prices and crop configuration were used to calculate the value of crop produce per ha, which was then used to calculate the viable farm size in the most basic scenario *B1: baseline yield*. This scenario only included value of produce of crops and no income from livestock or other sources. Scenario *B1: baseline yield* does not include any input costs (which were not incorporated in RHoMIS) and therefore underestimates the viable farm size. This issue was addressed in scenario *B2: baseline yield - costs*, where input costs were subtracted from the value of produce. Input cost were calculated for mineral fertilizer and for the seed of annual crops. These inputs are commonly bought in the area, although rates and use strongly differ among households (e.g., Tittonell et al., 2005). Information on input use, rates or costs per crop per household was not available from the survey. Fertilizer requirements per crop were calculated based on the baseline yield and the "soil supply yield": the yield obtained when no fertilizers are applied, which was derived from literature. For each crop, we assumed this soil supply yield to be the same as the lowest yield commonly obtained by farmers per site, while the baseline yield was the average yield commonly obtained by farmers per site. The difference between the baseline yield and the soil supply yield (baseline yield – soil supply yield) was then used to calculate fertilizer requirements based on nutrients concentrations in harvested product, the dry matter content and nutrient use efficiencies from literature. Only relevant macro-nutrients for fertilization were considered, e.g., N and P for maize and N and K for banana (East African highland banana in Uganda). Prices were based on the commonly used mineral fertilizers per crop and site. Costs for seed were based on commonly used varieties per site and advised sowing rates.

The crop intensification scenarios *I1: improved yields* and *I2: profitable crops I2: profitable crops* considered two options for intensification: increasing yields and cultivating more profitable crops. Scenario *I1: improved yields* uses the crop configuration of the baseline scenarios, while crop yields were increased to 50% of the water-limited yield. The costs of inputs were updated relative to scenario *B2: baseline yield - costs*, proportionally to the increase in yield. Fifty percent of the water-limited yield is considered as a possible goal for intensified crop production in SSA by 2050, which is needed to feed the burgeoning population (van Ittersum et al., 2016). Scenario *I2: more profitable crops* adds a crop area re-configuration, so that 20% of the cultivated area is allocated to the most common vegetable per site. Areas of other crops in the baseline crop configuration were scaled back proportionally.

Scenarios *B1, B2, I1,* and *I2* focused on the contribution of only crops to household income. In the study sites however, livestock and off-farm income are also important contributors to incomes. When other sources of income are available besides crop production, the contribution from crops to attain a living income can be smaller and hence a smaller farm area can be viable. Livestock requires land as well, but no information was available in the survey data about the private and/or common land used for livestock keeping and almost no fodder production was reported. We could therefore only include the value of livestock produce (reported in the RHoMIS survey) in our scenarios, and not its relation to farm area required. In scenario *O1: livestock income,* the current median number of tropical livestock units (TLUs) owned per household per site was multiplied by the median value per TLU per site as reported in the survey, to estimate the total value of produce of livestock per household and its effect on the viable farm size. In scenario *O2: off-farm income* current median off-farm income as reported in the survey was included and its effect of the viable farm size assessed.

Understanding Variation in Scenario Outcomes Among Sites

Site-specific values for each of the variables were used in calculating the viable farm size. To reveal which variables most strongly determined variation among sites in the scenario outcomes, we ran the model for calculating the viable farm size five times, once for each additional variable used in the calculations for scenario *B1: baseline yield*. In the first run, variable values (crops and crop allocation, yields, prices, living income threshold, household size) in all sites were set at the same value: the value for Rakai. In the next step, crops cultivated and their area allocation were made site-specific, so that the site-specific yields (for site-specific crops) could be investigated in next step. In every next step, one more variable was made site-specific, starting with variables that were more related to the cropping system: first yields, then prices, then the living income threshold, then household sizes. Relative differences among steps and among sites were compared to assess which variables most strongly explained differences in outcomes among the three sites. The order of the steps did not influence the analysis as we only compared the relative differences between steps and sites.

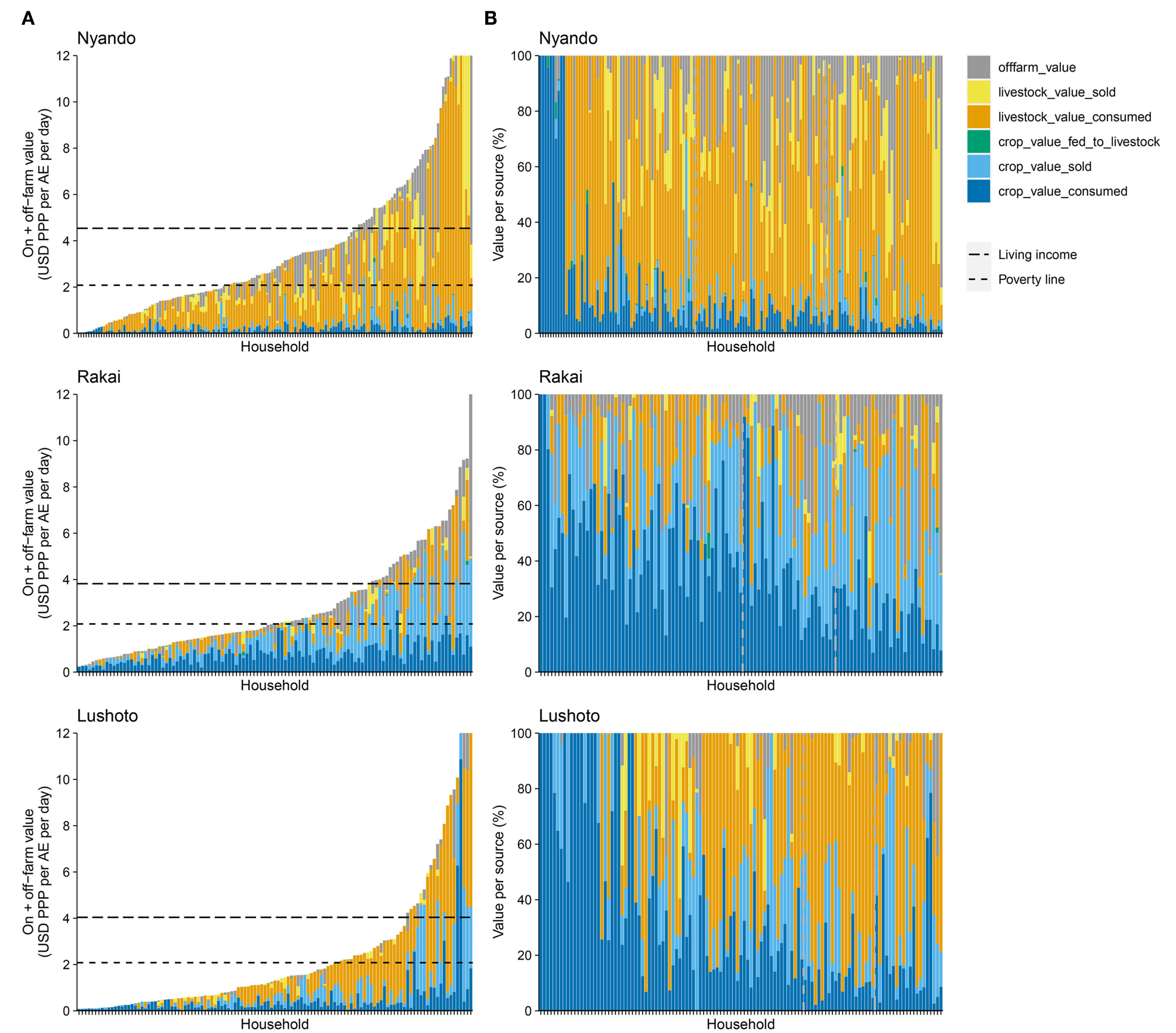

FIGURE 2 | Current household income in relation to the poverty line and living income benchmarks **(A)** and the relative contribution of different income sources to the current income **(B)**. Households in **(B)** are ordered the same as in **(A)**.

RESULTS

Current Income

Current Income From All Sources

When considering all sources of current household income, only 29% of the households in Nyando, 27% in Rakai and 17% in Lushoto obtained a living income (**Figure 2A**). The poverty line was reached by 61% of the households in Nyando, and just 50% in Rakai and 35% in Lushoto. At the left tail of the income distribution, crop produce for own consumption made the largest contribution to incomes in all three sites (**Figure 2B**). More than three quarters of the households had some off-farm income in Nyando and Rakai, while almost all households in Lushoto relied on farming only. In Nyando and Rakai, the contribution of off-farm income to the total household income was larger among households with a medium and high income than among households with a low income. Median off-farm income, for those receiving it, was also highest in Nyando (0.64 USD PPP AE^{-1} day^{-1}), followed by Rakai (0.32 USD PPP AE^{-1} day^{-1}) and Lushoto (0.23 USD PPP AE^{-1} day^{-1}), and see also **Supplementary Material 4**. No information was available from the survey about whether off-farm income sources were used to invest in farm activities. The contribution of livestock to value of farm produce was much larger in Nyando and Lushoto than in Rakai. In Nyando, the contribution of livestock was often larger than that of crops. This may largely be due to

TABLE 2 | Current livestock ownership and value of produce per TLU (tropical livestock unit).

Site	% of households owning livestock	TLUs owned per household[a]	Livestock value of produce per TLU (USD PPP TLU^{-1} year^{-1})	Livestock value of produce per AE[b] (USD PPP AE^{-1} day^{-1})
Nyando	100	8.8	322	1.48
Rakai	93	1.6	369	0.28
Lushoto	100	1.4	1,034	0.90

[a]*Median, calculated from the households owning livestock.*
[b]*AE, adult equivalents.*

the relatively large numbers of livestock—mainly cattle—kept in Nyando (**Supplementary Material 5**), at a median of 8.8 TLU per household compared to 1.6 and 1.4 TLU per household in Rakai and Lushoto (**Table 2**). The value of produce obtained per TLU was largest in Lushoto, however, where marketing dairy products is common, resulting in relatively high value of produce per TLU owned. In Rakai many households were holding pigs (**Supplementary Material 5**). Survey data revealed no relation between cultivated area and the number of TLU owned (**Supplementary Material 6**).

Value of Crop Produce

None of the households in Nyando obtained a living income from the total value of crops alone (**Figure 3A**). In Rakai 20% of the households and in Lushoto about 10% of the households obtained a living income from value of crops alone. Income from crops was generally highest in Rakai, where high-value perennial cash crops were more common. The most important crops in terms of value produced differed per site (**Figure 3B**). Maize was most important in Nyando and Lushoto, constituting 49 and 42% on average of the total value of crops, respectively. In Rakai coffee (29%) and banana (23%) were the most important crops in terms of value of produce. Some other specific crops, that were important per site are sorghum (13%) and sugarcane (7%) in Nyando, Irish potato in Rakai (11%) and Lushoto (10%). Beans were common in all three sites and most important in terms of value of produce in Lushoto (23%). Among households that obtained a low total value of crops, specific crops were relatively more prevalent: sorghum in Nyando and beans in Lushoto.

Farm areas and the total value of crop produce were unequally distributed (distributions shown in **Supplementary Material 4**). In Nyando and Rakai, those who obtained a larger value of crops (>85 percentile) tended to have larger farms than those who produced less crop value (**Figure 4**).

Viable Farm Size

Scenario *B1: baseline yield* resulted in viable farm sizes of 2.5, 2.0, and 1.6 ha for Nyando, Rakai and Lushoto, respectively (**Figure 5**; **Supplementary Material 7**). This was a three-fold difference with the current median cultivated area in Nyando (0.8 ha) and a two-fold difference for Lushoto (0.8 ha), while for Rakai the viable farm size was similar to the current median cultivated area in Rakai (1.8 ha). The relatively small viable farm size estimate for Lushoto can be explained primarily by the combination of relatively high-value crops (see effect of variation in crops and crop allocation, Step 1, **Table 3**), and the smallest median household size of all sites (Step 6), which both result in a smaller viable farm size. In Nyando, crop prices were relatively low (Step 4), while the living income was relatively high (Step 5), resulting in a relatively large viable farm size. Crop prices were most favorable in Rakai (Step 4), e.g., beans were most expensive in Rakai, although less than double the price in the other two sites. Yield differences had the smallest effect on the variation in outcomes among the three sites (Step 3).

Including basic input costs of fertilizer and seed (scenario *B2: improved yields - costs*) had a strong effect, as it resulted in a 30, 20, and 25% larger cultivated area needed to attain a living income than in the previous scenario without input costs (scenario *B1: baseline yield*) in Nyando, Rakai, and Lushoto, respectively (**Figure 5**).

The crop intensification scenarios strongly reduced the viable farm sizes. Increasing yields to 50% of the water-limited yield (scenario *I1: improved yields*) had the largest effect and resulted in viable farm size estimates that were three times smaller than in scenario *B2: baseline yields - costs* (**Figure 5**). Allocating 20% of the cultivated area to the most common vegetable per site (scenario *I2: profitable crops*) resulted in a larger area reduction in Rakai and Lushoto than in Nyando due to the higher gross margin of tomato and cabbage in Rakai and Lushoto, respectively, as compared to kale in Nyando. Vegetables however, currently only occupied a minor part of the cultivated area and only few households had >20% of their cultivated area under vegetables: 6, 15, and 9% of households in Nyando, Rakai, and Lushoto, respectively, and these were commonly the households that obtained a high value of crop produce (**Figure 3**).

Including livestock as an additional income source (scenario *O1: livestock income*) had only a limited reducing effect on the viable farm sizes, in comparison to the crop intensification scenarios (**Figure 5**). The largest effect was found in Nyando, where the number of cattle owned was relatively large (**Table 3**). This cattle was likely sustained from grazing on common land around nearby streams and wetlands. Households in Rakai and Lushoto owned much fewer TLUs on average and therefore had less income from livestock (despite the relatively high value per TLU in Lushoto, due to dairy marketing). The estimates of the viable farm size therefore decreased only very little. Including off-farm income as a contributor to a living income (scenario *O2: off-farm income*), again resulted in a relatively large decrease in the viable farm size in Nyando (**Table 3**). The sum of income from livestock and off-farm sources was USD PPP 2.12, which is more than the poverty line, indicating the importance of alternative income sources in Nyando. Income from crops would not be required to reach the poverty line, with median incomes from livestock and off-farm sources in Nyando, but a living income was not reached with these non-crop sources only. Including off-farm income had only a small effect in Rakai and Lushoto.

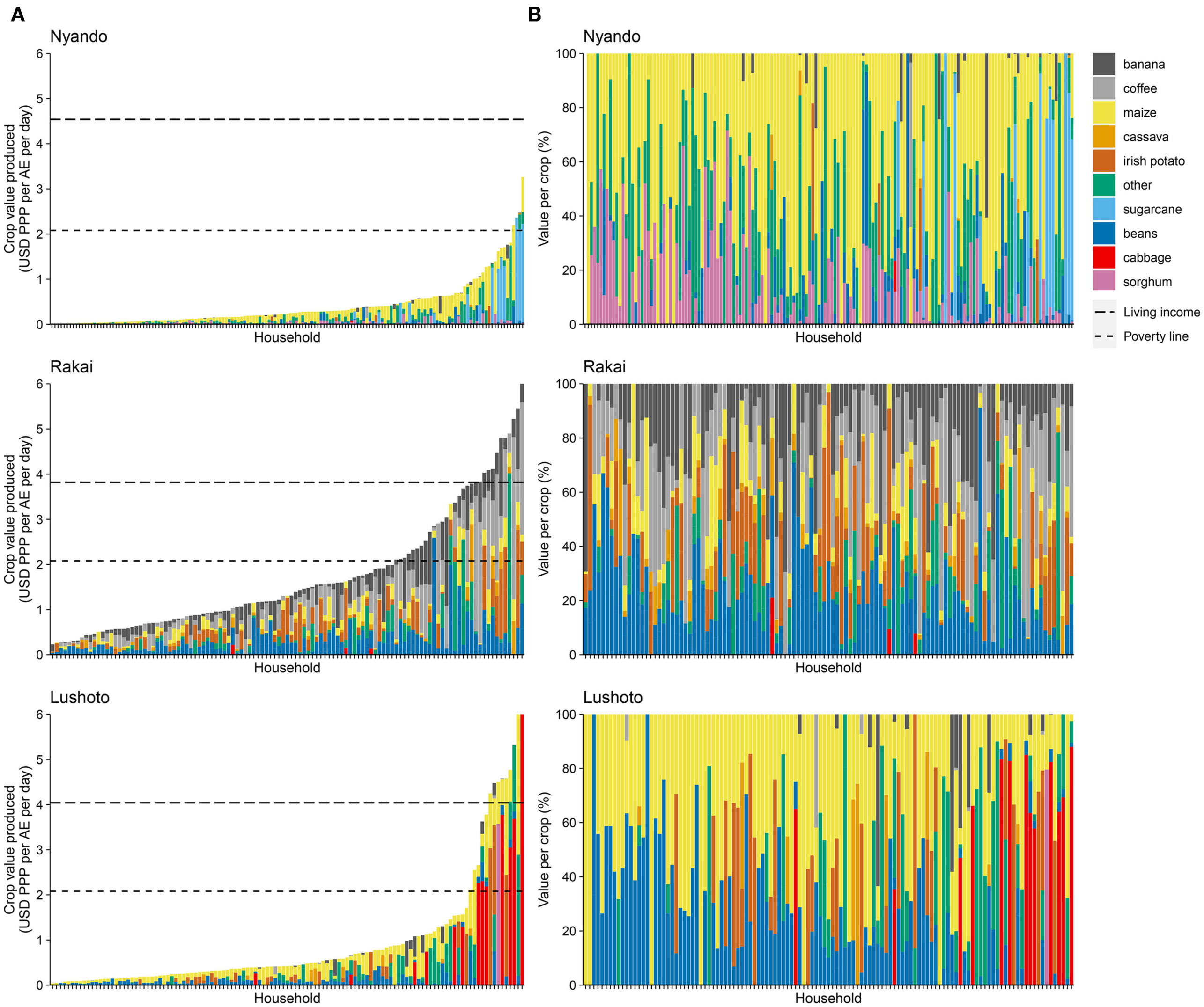

FIGURE 3 | The current value of crop produce in relation to the poverty line and living income benchmarks **(A)** and the relative contribution of different crops to the total value of crops **(B)**. The value of crop produce is the sum of the value sold, consumed and fed to livestock. Households in **(B)** are ordered the same as in **(A)**.

Comparing Viable Farm Areas With Current Cultivated Areas

By comparing viable farm sizes with the current cultivated areas we assessed what proportion of the current population would be able to attain a living income with their current farm area, for each of the scenarios. Because the scenarios were incremental, every next scenario resulted in a smaller estimate of the viable farm size (except scenario *B2: baseline yields - costs* which incorporated costs) and a larger number of households in the study populations had access to the estimated viable farm size. This number strongly depended on the shape of the distribution of current farm sizes (**Figure 6**), which was skewed toward smaller farm sizes in Nyando and Lushoto. In each of the sites, a small proportion or none of the households currently cultivated an area larger than the viable farm sizes of the baseline scenarios (*B1: baseline yield*, *B2: baseline yields - costs*). In the conservative scenario *B2: baseline yields - costs* this was 0, 27, and 4% for Nyando, Rakai, and Lushoto, respectively. The yield-improvement scenario (*I1: improved yields*) decreased the viable farm size so much in Rakai and Lushoto, that it covered the flattest part of the curve with a major shift in the proportion of the population having a viable farm size, 92 and 70% in Rakai and Lushoto, respectively. In Nyando, apart from crop intensification, income from livestock was required (scenario *O1: livestock income*) for the majority of the study population (73%) to be able to attain a living income from their currently cultivated area.

DISCUSSION

We first compared current smallholder farmers' incomes in three sites in the East African highlands with the living income benchmark. We then assessed what area would be required to attain a living income from smallholder

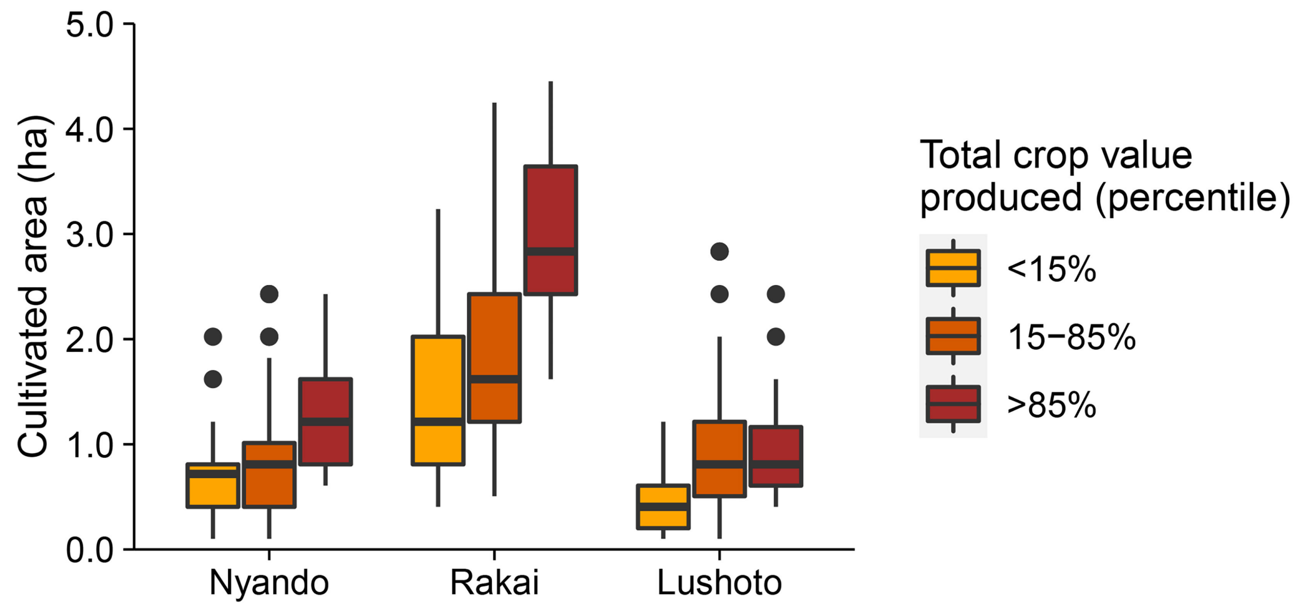

FIGURE 4 | Cultivated areas for households in relation to a low (<15 percentile), medium (15–85 percentile) or high (>85 percentile) current total value of crop produce.

TABLE 3 | Viable farm sizes without or with the site-specific values per variable that were included in estimating the viable farm size, using scenario *B1: baseline yields*.

Site	Viable farm sizes (ha)					
	Step 1: crops and allocation yields prices living income household size	Step 2: *crops and allocation yields prices living income household size	Step 3: *crops and allocation *yields prices living income household size	Step 4: *crops and allocation *yields *prices living income household size	Step 5: *crops and allocation *yields *prices *living income household size	Step 6: *crops and allocation *yields *prices *living income *household size (full B1 scenario)
Nyando	2.0	1.9	1.9	2.4	2.8	2.5
Rakai	2.0	2.0	2.0	2.0	2.0	2.0
Lushoto	2.0	1.5	1.6	2.0	2.1	1.6

In step 1, values were set at the values for Rakai, for each variable. In each subsequent step, one more variable was set at its site-specific values. Asterisks indicate the variables for which site-specific values were included.

farming—the viable farm size—and compared this with current cultivated areas. We explored six incremental scenarios, which included intensification (increased yields and a change in crop configuration) and other sources of income (livestock and off-farm). For each scenario, we estimated the viable farm size. This study is the first that uses the living income as a benchmark for establishing what would be a viable farm size. It builds on earlier work in SSA that used the poverty line as a benchmark (Harris and Orr, 2014), and similar historical assessments of what would be "decent" incomes for farmers in Europe after the second world war (Van Merriënboer, 2019). Such calculations are still made by the European Union to estimate subsidy requirements for farmers' incomes to be comparable with non-farm jobs in the EU (2020). Our results explored viable farm sizes but do not provide a precise answer to the question what a future farm size would need to be, as the analysis is based on simple assumptions and does not consider all complexities of making a living from farming. The scenario with baseline yields and input costs (scenario *B2: baseline yields - costs*) was the most conservative, providing a first rough estimate of what a viable farm sizes would be under current production levels and market prices for an average sized family: 3.6, 2.4, and 2.1 ha for Nyando, Rakai, and Lushoto, respectively, which is 4.5, 1.3, and 2.5 times the current, median cultivated area in the three sites. Currently, only 0, 27, and 4% of the population had a cultivated area that was larger than the viable farm size in scenarios *B2: baseline yields - costs*, in Nyando, Rakai, and Lushoto, respectively. Current cultivated areas were large enough for most households to attain a living income only in the intensification scenarios for Rakai and Lushoto (**Figure 6**). For Nyando a living income could not be attained unless other sources of income, i.e., livestock, were also included. This indicates that the cultivated area per household

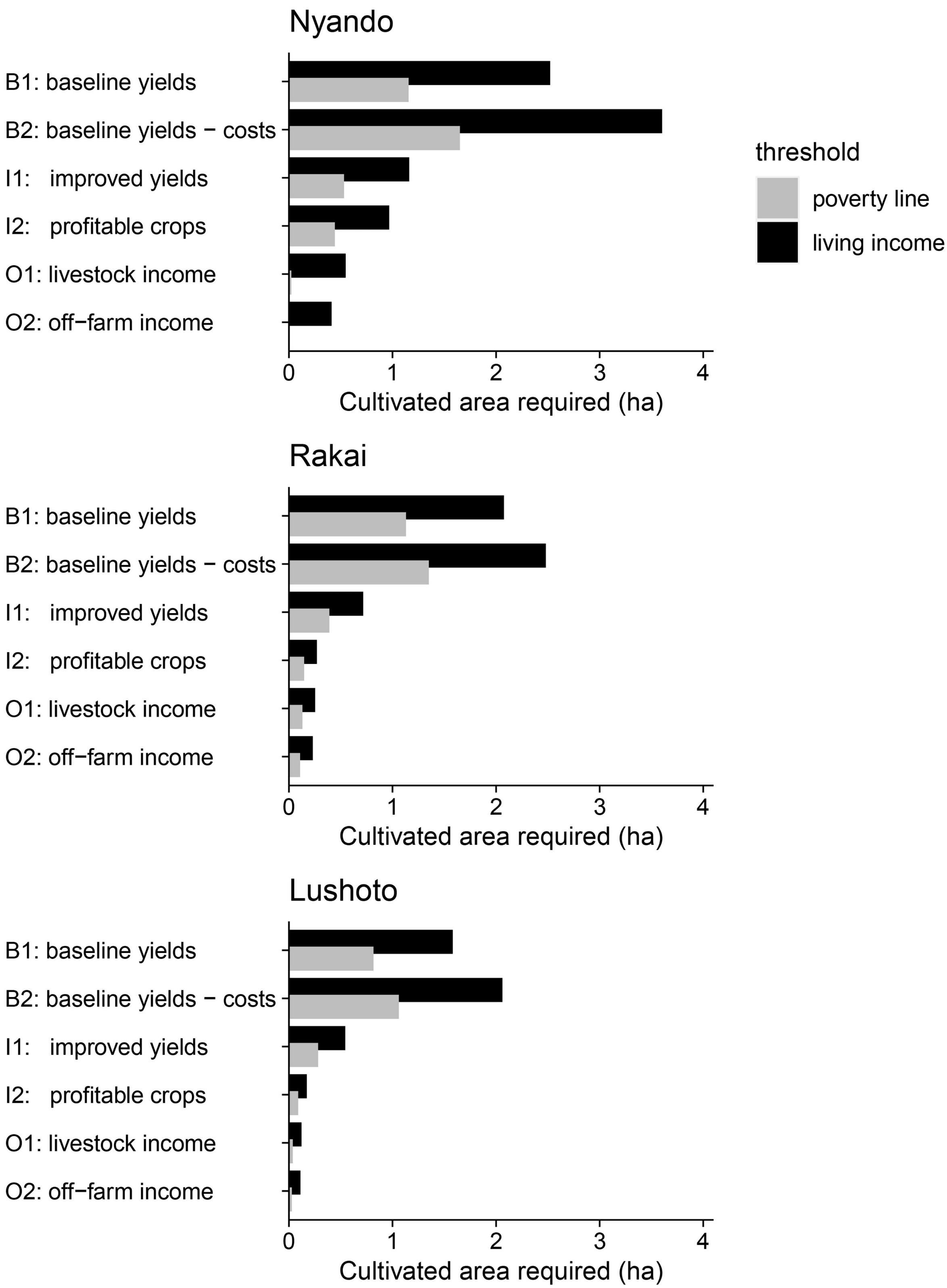

FIGURE 5 | The cultivated area required to reach the poverty line or obtain a living income (viable farm size) for a household of median size for six scenarios. All scenarios are incremental, meaning that each scenario builds on all improvements and assumptions of the previous scenario.

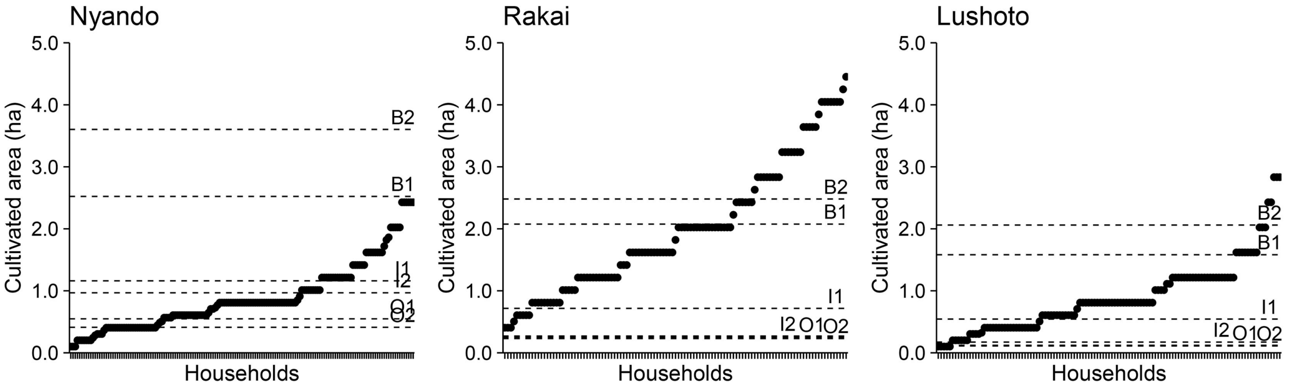

FIGURE 6 | Distributions of current cultivated areas per household as reported in the survey, and the cultivated area required to attain a living income (viable farm size; dashed horizontal lines) for six scenarios. Full scenario names: *B1: baseline yields, B2: baseline yields - costs, I1: improved yields, I2: profitable crops, O1: livestock income, O2: off-farm income*.

would have to increase and/or that cropping systems would have to intensify considerably for farming households to attain a living income from farming.

Current Smallholder Incomes

The analysis of current income clearly showed the limited value that is currently accrued from cultivating crops, with currently only 11% of the households obtaining a living income from crops in Rakai, while this held for 8% in Lushoto and none of the households in Nyando. Smallholder farmers relied on diverse livelihood activities besides crop cultivation, although poorer households tended to rely primarily on cropping, i.e., the 5–15% of the households with the lowest household income. With all income sources combined, only 29% of the households in Nyando, 27% in Rakai and 17% in Lushoto obtained a living income, based on the survey data. Crops contributed only to part of the total household income and this contribution strongly varied per site. Considering crops alone, at best, <20% of the households currently obtained a living income (Rakai), while none made a living income in Nyando. Households with low total household income often depended solely on farming and used the largest part of their farm produce for home consumption. This may imply that investing in crops and obtaining a good income from crops alone is difficult in current farming systems. In order to increase yields and intensify, farmers need viable options in which to invest (Vanlauwe and Dobermann, 2020). Livestock and off-farm income were most important for household income in Nyando, with all households having livestock and 63% of households having off-farm income. In all three sites, these sources of income were primarily important for households with a relatively higher income. The importance of livestock and off-farm income as an income source for better-off households in the study sites is in line with earlier studies (Frelat et al., 2016; Wichern et al., 2017; Waha et al., 2018). Among the households that obtained a low total value of crops, staple crops were common (beans in Lushoto, sorghum in Nyando), rather than high-value cash crops (sugarcane in Nyando). It is unclear from the data whether the production of low-input, low-value crops was the result of preference or necessity. Limited opportunity to invest or access markets could be major constraints for possible improvements like sustainable intensification, for these households. The sparse contributions of off-farm sources to incomes in Rakai and Lushoto point to the limited current off-farm opportunities in rural areas in SSA (Headey and Jayne, 2014). Toward the left tail of the income distribution graphs, reported incomes were very low and often well below the poverty line and the living income. This suggests that the survey data may have under-reported current household incomes. Under-reporting of incomes is a common problem in this type of surveys (Fraval et al., 2019) that may be partly explained by food sharing among households during the lean season when food stocks start to run out (Djurfeldt and Wambugu, 2011), something that was not captured in the survey. Livestock holdings seemed not to be related to farm area, and fodder production was only reported a few times in the survey. Additional, more specific, data on land use by livestock is needed to assess the potential role of livestock in providing a living income, in relation to the area that is cropped.

Viable Farm Sizes to Attain a Living Income

Our analysis showed that current farm areas are in most cases too small to attain a living income from farming, if no changes in cropping systems are made. For instance, only 0, 27, and 4% of the households had a current farm area that was the same or larger than the viable farm size in the scenario *B2: baseline yields - costs* in Nyando, Rakai, and Lushoto, respectively (**Figure 6**). This means that for farms to be viable, the area under cultivation needs to be increased and/or production intensified. There was a large gap between yields of major crops in the baseline scenarios and the improved yields in the intensification scenarios (50% of the water-limited yields), which were more than three times larger. Hence, the estimate of the viable farm size was also reduced by a factor three approximately in scenario *I1: improved yields*, compared to scenario *B2: baseline yields - costs* (**Figure 5**). This meant that 27, 92, and 70% of the households currently had a farm area that was the same or larger than the viable farm size in Nyando, Rakai, and Lushoto, respectively (**Figure 6**). Intensification to yield levels that were 50% of the water-limited yield (as in the *I1: improved yields* scenario) is possible at farm level in western Kenya, e.g., by providing a USD 100 input voucher per season (Marinus, 2021). Our results are therefore slightly more optimistic than those of Harris and Orr (2014), who looked at the impact of options for agronomic improvement at household level. They found that these improvements would not raise most households above the poverty line because cultivated areas were too small. Their analysis, however, did not consider income from livestock, nor areas with high-value crops such as banana, coffee and vegetables, although they considered variable costs in detail (e.g., labor). Among the study sites, crops were least profitable in Nyando, and it would be a challenge to attain a decent living from crops alone with current farm areas. Including livestock value of produce in Nyando, a living income could be attained with current farm sizes, i.e., 73% of the households had a current farm area that was the same or larger than the viable farm size in scenario *O1: livestock income*. By including only basic input costs (seed and mineral fertilizers) and no other costs in our study, we may have overestimated incomes from farming, and hence underestimated the farm size required to provide a living income. This and our other assumptions (e.g., using median yields and seasonal cropping patterns from literature) were made on the grounds of data availability and quality. Further research would be required to provide more detailed estimates, preferably from on-farm studies, to assess the profitability of crops across farms, the yields that can be attained, and the input costs required. Our calculated viable farm sizes should therefore be seen as minimum viable farm sizes, which likely need to be larger if other costs and other limiting factors such as production risks (e.g., due to price or climate variability) would be included.

Scenarios were based on the baseline crop configurations, up to scenario *I2: profitable crops*. This choice was data-driven. We realize that once people gain investment capacity, their livelihood strategies may change, and they might move toward more capital-intensive farming strategies. Some of the crops in the baseline crop configurations are currently cultivated because they can provide at least some yield with low inputs, for instance cassava (Fermont et al., 2008). Once higher incomes are achieved, such crops may be replaced by more profitable crops. Opportunities for cultivating high-value crops however, are limited as crops such as vegetables often have a limited demand, high input cost and highly varying prices. Moreover, suitable land for cultivating vegetables is limited, which also explains why currently only few households cultivated vegetables on more than 20% of their cultivated area. Vegetables, for instance, are cultivated only in inland valleys in Lushoto because of water availability, which limits the options to increase the cultivated area with vegetables (Sakané et al., 2013). Once production levels and/or the types of crops produced change, market prices will change as well, as was for instance found when maize production increased in Ethiopia (Spielman et al., 2010; Abate et al., 2015). Such fluctuations would again influence the profitability of the scenarios explored. For the case of vegetables in particular, demand may be fairly inelastic.

Expanding Farm Sizes and/or Intensifying Production? Implications of Moving Toward Viable Farms

A large proportion of the study population did not have a viable farm size. With intensification however, a decent income appears to be within reach on the farm areas that were cultivated at the time of the survey. To attain a decent living, farming households could therefore expand and/or intensify production, or combine both options (Giller et al., 2021). All choices would require substantial changes at farm level, and it is unlikely that these options are either feasible or attractive for all. Intensification and/or expansion may only be achieved when supportive measures are in place, such as input subsidies. Moreover, such strategies would only be relevant if they are in line with households' objectives and aspirations: do they pursue farming as a livelihood strategy, or seek alternative employment, or a combination of the two (e.g., LaRue et al., 2021; Sumberg et al., 2021)? Supportive measures should also consider that intensification and/or expansion of production could influence inequalities within households, where women often have less access to land or control over production resources and outputs (Beuchelt, 2016; Tavenner et al., 2019).

We assessed the farm area required at household level, while only considering capital through a simple assessment of input costs. More elements of farm structure—labor and capital—however, would have to be dedicated to intensification and/or expansion. Although the use of inputs such as mineral fertilizer and improved seed can be profitable in current smallholder farming systems, their use is often limited (Nin-Pratt and McBride, 2014). Increasing yields to 50% of the water-limited yield, would require considerable increases in input use: the N fertilizer requirements in scenario *I1: improved yields* for instance, were three to five times larger than at baseline yields. Such an increase in input use may require input subsidies (Jayne et al., 2018), along with other supportive policies such as price protection and improving access to markets (Wiggins, 2016; Koning, 2017), which together have shown to be able to increase yields to 50% of the water-limited yield at farm level (Sanchez et al., 2007; Marinus, 2021). Also Fraval et al. (2018) found that considerable improvements in farm performance can happen in a relatively short time span of three years for part of the population. Increasing the cultivated area of a farm would require more efficient labor use. Labor constraints explain part of the current yield gap (Silva et al., 2019), and current crop choices of farmers might become more labor-constrained on larger areas. Small-scale mechanization may therefore be required to improve labor productivity (Van Loon et al., 2020), in particular if farm areas would increase to attain a living income. Lastly, apart from land, labor and capital, additional knowledge will also be needed when moving toward for instance scenario *I1: improved yields*. Marinus et al. (2021) for instance describe how farmers required knowledge on specific intercropping arrangements for maize and legumes when maize growth became prolific—reaching 50% of the water-limited yield level—and thereby smothering intercropped legumes.

At the national or regional level, if farms would grow in area to attain a living income from farming, there is insufficient land available for all households without massive expansion of the area under agriculture. For instance, moving from current farm areas to the viable farm areas as calculated in scenario *B2: baseline yields - costs*, would require farm areas that are 440, 130, and 260% that of the current, median cultivated area in Nyando, Rakai, and Lushoto, respectively. Hence, for all farming households to be able to attain a living income, off-farm employment would be needed for those who leave farming (Koning, 2017; Giller, 2020). In the study sites, off-farm income sources contributed less to incomes than crop and livestock production. Land is currently unequally distributed, and the poorest and smallest farms are in an unfavorable competitive position (Chamberlin and Jayne, 2020). Competition for land may further marginalize the smallest farms in future, while the largest grow (Headey and Jayne, 2014; Jayne et al., 2014, 2021).

Concluding Remarks

Our study is the first to use the living income to establish what would be a "viable farm size," as a benchmark for smallholder farming. We applied the approach in three sites with contrasting farming systems and explored scenarios, which considered crop intensification strategies, income from livestock and off-farm income to explore which households could achieve a living income. With current yields, cultivated areas would have to increase considerably to attain a living income from crops: for instance to more than four times the median cultivated area in Nyando. Intensification scenarios indicated that feasible yield increases would lift 70% of the households to a living income on their current cultivated area. Only in Nyando would also other sources of income, such as livestock, be needed for the majority of the population to attain a living income from farming. Households who are unable to earn a living income from farming would need social protection for the poorest, and alternative employment for those who choose to step out of farming.

In this study we highlight the current constraints faced by farming households, rather than to propose the explored scenarios as pathways for rural development. Clearly fundamental changes in the institutional and policy environment are needed to address both rural poverty and the need to increase agricultural productivity to meet the national food demand of countries in SSA in the face of rapid population growth. The viable farm size methodology may be a useful tool in understanding what is required for smallholder farming to provide a decent living.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://doi.org/10.1038/s41597-020-0388-8.

ETHICS STATEMENT

The data originated from van van Wijk et al. (2020), who state the following: the data collection efforts conformed with the principles of the 1964 WMA declaration of Helsinki. Ethical approvals for the survey applications was obtained by the Internal Ethical Review Committees of the different institutes [e.g., the Internal Review Ethics Committee (IREC) of the International Livestock Research Institute] or for those partners without an Internal Ethical Committee, by ethical evaluation by the senior management at each organization after careful evaluation of the content, methodology, and with oral informed consent statement built-in to the survey. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

WM, ET, MW, KD, GV, BV, and KG designed research and wrote the paper. WM and ET performed research and analyzed data. MW supplied data. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2021.759105/full#supplementary-material

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Heterogeneity of Resilience of Livelihood Strategies in Pastoral and Agropastoral Farming Systems of Rural Semi-arid to Arid Areas in Morocco

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A large proportion of rural households, particularly in the dry land areas, representative for more than 10% of the world's land surface and up to 80% in Morocco, depend for their livelihoods on livestock. They exploit livestock's capacity to live in very harsh environments using herd-mobility at multiple scale level. Understanding the multiple contributions of livestock to the household and national economy raises complex research issues and challenges linked with the multitude of goods and services derived from livestock, their interactions with other family activities, and the local and national context. The objective of our research was therefore to analyse the diversity and assess the resilience of livelihood strategies of farming households oriented to livestock using a set of data collected in the dry land areas (oases and mountainous zones) of Morocco and discuss the livelihood outcome indicators. To achieve this, we have realized a cross-sectional analysis of livelihoods and adaptive capacity, to select a set of pertinent indicators. These indicators have been developed using an adapted version of the Rural Household Multi-Indicator Survey (RHoMIS) toolkit for pastoral and agropastoral household systems. Our results highlight the critical importance of livelihood diversification (off-farm diversification, livestock diversification, and crop diversification) in building household resilience and the livelihood outcomes. While livelihood strategies undoubtedly contribute to livelihood outcomes, there is also a critical iterative process, i.e., livelihood outcomes also influence the livelihood strategies at the farming households. The present work proposes an aggregated indicator of livelihood outcomes allowing us to capture the heterogeneity of living conditions of agropastoral systems by considering the main drivers of this system, *i.e.*, mobility, livestock species, and physiological stage composition of the herd. This approach could constitute a valuable contribution to help fill the knowledge gaps that do not allow policy makers in developing contextualized rural development policies and instruments in these very harsh environments.

Keywords: resilience profile, livelihood strategies, agropastoral system, RHoMIs, capacity of actions, multi-indicators approach, Morocco

INTRODUCTION

The concept of resilience has grown in importance extending from addressing the ability of groups or communities to cope with external stresses (Adger, 2000) but also the capacity to "bouncing forward" [as described by Davoudi et al. (2012)], up to understanding, managing, and governing complex integrated systems of people and nature [see the works of the Stockholm Resilience Center, such as Janssen and Ostrom (2006) or Folke (2016)]. In this resilience thinking, the main challenge is to capture the dynamics and capacity to survive (adaptability) and evolve (transformability) under contexts of local governance (Meuwissen et al., 2019). During the last decade, this concept has come to form a key entry-point to assess the sustainability of systems, i.e., the dynamics and ability to endure in an environment that is changing like in the drylands (e.g., Haddad et al., 2021). Nowadays, we can distinguish two main streams around this approach of sustainability based on resilience. In the first stream, applied at the local level, the assessment of resilience essentially requires an understanding of the stocks and diversity of assets in terms of complementarities and the ability to innovate, change or adapt. This approach has been formalized within the well-known "Sustainable Livelihood Framework," providing a set of quantitative and qualitative indicators that ranged from resource endowment to resource use and passing through the means and rights of access to these resources. Applied to dryland systems, this framework was mainly based on access to current and potential resources ("entitlement") of individuals estimated from the assets and their production, and reciprocal arrangements (share capital, rights, and obligations, also called claims) (Scoones, 2009; Li et al., 2017). Overall, these indicators attempted to encompass a loss of security, affecting the level of well-being at the individual or local level. In the second stream, the research focuses on the nature of capacities, i.e., buffers, adaptive or transformative, to capture the overall ability of the studied system to resist, adapt or reorganize in the face of a set of perturbations (See Berkes et al., 2003; Walker et al., 2004; Darnhofer et al., 2010; Folke et al., 2010; Darnhofer, 2014). This approach shows the interactions, complementarities, or substitutions between the farm and off-farm activities by focusing on the diversity of capacities. Here, resilience is viewed as a process more than as an outcome in facing perturbances.

The resilience thinking applied to pastoral and agropastoral systems has led to a multiplicity of recent research on adaptive capacity and adaptation allowed by livestock and range management' decision making (Leach et al., 2007; Adger et al., 2009; O'Brien and Wolf, 2010; Eakin et al., 2014; Vermeulen et al., 2018). Notably, Vermeulen et al. (2018) highlighted a set of case studies demonstrating the potential roles of livestock through its multiple functions on the adaptive and transformative capacities of the (agro) pastoral systems. In reference to socio-ecological approaches, the resilience concept has also received significant interest over the past decade, considering the complexity of ecosystems and their inter-relationships with social networks (McAllister et al., 2006; Linstädter et al., 2016). Nevertheless, many research challenges remain with regard to understanding and assessing the adaptive capacity and therefore resilience of farming households who live off livestock income in dryland areas. Some authors such as Abebe (2020) or Melketo et al. (2021) emphasized the effect of location specific factors in determining resilience of family systems based on livestock activity. The multiple roles that livestock play in livelihood strategies and outcomes (e.g., safety capital and productive asset) and the role of complementary activities such as crop cultivation or off-farm activities, still remain important aspects that would benefit from further investigation (Alary et al., 2011).

Moreover, one common measure of the livelihood outcome at national and international level is the Progress out of Poverty Index®(PPI) (Grameen Foundation, 2014). However, it remains to be seen how appropriate this poverty index, based on 10 indicators related to living conditions (such as type of house, rooms number, family size, etc), is for pastoral and agropastoral family systems based on mobile living conditions. McPeak et al. (2011) proposed a livelihood measure derived from data on cash income from livestock activity with the earnings resulting from direct and indirect gifts and transfers due to social activities around livestock. Here we propose to build a livelihood measure based on herders' perception that we will compare to the PPI index.

The objective of our research was therefore to analyse the diversity and assess the resilience of livelihood strategies of farming households oriented to livestock using a set of data collected in the dryland areas of the oases and mountains of Morocco. To achieve this, we adopted the core modules of the RHoMIS toolkit (see Hammond et al., 2017) of which we added a specific module related to herd management in association with herd-mobility and herd contribution to family livelihood in terms of food security, cash flow or net safety. This new sub-module aimed to adapt the current RHoMIS survey toolkit to (agro) pastoral systems. Furthermore, we adopted the conceptual framework of sustainable rural livelihoods that facilitates the analysis of challenges related to rural development, poverty reduction, and environmental management in rural contexts (Scoones, 1998, 2009). Working at the farm and household level, we used multiple correspondence analyses (MCA) on household asset variables and variables related to livelihood diversification and social management to develop a set of rural livelihood strategy types. We then characterized and compared resilience profiles with livelihood outcomes among these types by developing a set of resilience components based on formal and informal interviews with village elders and key local stakeholders. We proposed two approaches for livelihood outcomes, one based on PPI and the second on the criteria of living conditions used by the studied communities.

The adaptive capacities were assessed not only through the diversity of capital assets but also in regard to herd-mobility management, social transfers and gender involvement at the household level. The herd-mobility management was considered as both an outcome of social capital and indicator of the pressure on the resource at farm and territory scales. The social transfers included the majority of the loans or gifts given and received at the household level although the gender involvement in (agro) pastoral systems covered the domain of the decision and task management at the household level by identifying the women and young' control on different herd management activities. The mobility of pastoralists exploiting the animal feed resources along different ecological zones is usually considered as a flexible response to a dry and increasingly variable environment (FAO, 2018). We will analyse data from two contrasting dryland regions in Morocco. By better understanding the current pastoral and agropastoral systems in these regions as well as their resilience, we aim to help identify different pathways for future development of mobile livestock activities, an activity that is considered to be a significant opportunity in the face of growing sustainability risks in the region.

MATERIALS AND METHODS

Description of Study Areas

To cover a diversity of pastoral and agropastoral conditions, we selected two contrasting case studies in Morocco, based respectively on camel farming systems in the desert zones in southern Morocco (region Guelmin-Oued Noun), and on sheep and goat systems in the mountainous regions at the margins of an oasis region (Dadès valley, Tinghir province). In these two study areas, the farm and household systems are organized around livestock systems based on mobility. It is notable that in both regions, there is an increasing trend toward livelihood diversification to off-farm and agricultural activities associated with children's education and the aspirations of the young generation. **Figure 1** presents the two study areas that were selected to reflect the agroecological diversity in pastoral systems in rural Morocco.

Historically, Guelmim-Oued Noun region was an important location along the trading area for the collection, redistribution, and transit of goods between the south and the north of the Sahara (Attou and Belkadi, 2014). Since the 1950s, camel production has recorded an important period of decline, closely associated with political and social reconfigurations of the country, agricultural modernization in the desert oases (Lazarev and Kadi, 2012), and successive conflicts (Martin, 2011). In 1956, there were an estimated 250,000 camel heads in the region of Guelmim-Oued Noun, declining to 100,000 in the 1970s, and then to less than 50,000 in the 1980s. With regional governmental support in the 2000s and the Green Morocco Plan in 2008, the camel sector has been earmarked as an essential agricultural sector in the South. In 2013, the camel population was estimated at around 200,000 heads (Mahdi, 2015). Surveys took place in and around Guelmim city and the rural community of Tuflit, located 25 km east of Guelmim city, Guelmim province. Its central position and links with the regional weekly market of Amhirich in Guelmim city for live animals is an important feature of this community (see map 1). Guelmim-Oued Noun's region comprises 4 provinces: Sidi Ifni, Assa Zag, Guelmim, and Tan Tan. With the exception of the province of Sidi Ifni, due to its mountainous relief oriented to the ocean, the provinces are characterized by an arid, Saharan climate with dry, hot summers and cold winters. The region's geomorphology is dominated by mountainous areas (corresponding to the prolongation of the Anti-Atlas from north to northeast) and semi-desertic areas with plains. The average annual rainfall is between 40 mm in Assa Zag to 120 mm in Guelmin province. Across the governorate, agriculture accounts for only 3.3% of the total land area, compared to 51.4% for pastureland and 40.8% for wastelands. The remaining land-use is mainly forest. This explains the predominant presence of camels, sheep and goats in this environment.

The second study area is located in the province of Tinghir at the intersection between the desert zones and the foothills of the Haut-Atlas. Tinghir covers a large diversity of agro-climatic environments from the rainfed plains to mountainous areas and oases. The province is characterized by a dry climate, with an average annual rainfall of 90 mm in the South and 200 mm in the north at higher altitudes. Snowfall is sometimes recorded in the high mountains from a peak of around 1,800 m (municipality of M'semrir). Rainfall often results in flash flooding of the oueds (dry river beds), causing losses to hydro-agricultural infrastructure and cultivated land. Very high temperatures in summer (over 40°C) and very low in winter (down to −5°C) are recorded, accompanied by strong windy events (Statistical Yearbook of Morocco, 2016). The province of Tinghir is crossed by a few temporary rivers (*oueds)* and hydraulic basins. The agricultural and cultivated area accounts for about 1% of the provincial territory (12,800 ha) and is only possible with access to irrigation water. Landholdings are small, with average land ownership of 0.6 ha, underlining the trend toward land fragmentation in the region. The main annual crops include cereals (wheat and barley), alfalfa, and vegetables. The province is also known for its almond and olive trees and, more recently, apple plantations. Livestock activity based on sheep and goat grazing system constitutes the main farming activity accounting for over 98% of the territory.

Data Collection and Sample

Data collection was supervised by senior researchers and organized by a research team accompanied by university students, technicians and local extension agents in the two study areas. The sampling approach was guided in view to

FIGURE 1 | Location of the two study areas in Morocco. White dots with black points indicate location of surveys (maps created using Google Earth).

capture the diversity of farm systems. Two criteria were selected: the camel-herd size in Guelmin and the geographical gradient along the Dadès valley in Tinghir. Then, we followed the snow ball sampling approach to identified the household farms in each category.

The data collected in Guelmin province was performed between April and August 2019. Fifty households were surveyed, subdivided between the city of Guelmim (4 households) and the rural area of "Tûflit" (46 households). The surveys conducted in the city of Guelmim were carried out directly with the herders in their homes. The household surveys in "Tûflit" were carried out either in the herders' tents and their families or in the grazing area (Noel, 2019). In Tinghir province, 36 household surveys were conducted between February and March 2020 along the valley of Dadès from the high elevation zone (1,200 m) to downstream of the valley in the direction of the oasis zone (Hrara, 2020). Our targeted groups were the pastoral and agropastoral systems based on small ruminants such as sheep and goats and few camels.

In addition, complementary interviews were conducted with key local stakeholders. The majority of them held a leadership position at the tribal or communal level as *cheikhs* (local tribal representatives) or president of the communes in Guelmim province and local authorities in Tinghir province. These interviews were open discussions in order to provide greater insight into the farming systems in the area, changes over time, and in particular, differences in living conditions and livelihood outcomes, that constituted the basis to build the livelihood outcome indicator.

We recognize that our sample can appear very small (total 96 households) compared to other studies. However, our sampling approach was reasoned to capture the diversity of farm systems based on open interviews with representative stakeholders. Moreover, our intention was not to conduct econometric analysis but mainly understanding the livelihood strategies and see how to improve the RHoMIS survey toolkit to apprehend these (agro)pastoral systems. We have also privileged open interviews in order to discuss indicators generated from data collection using RHoMIS adapted to this context through a new module regarding mobile herd-management.

Adapted Farm Household Survey Based on RHoMIS Survey to Pastoral and Agropastoral Systems

The household farm survey was based on a structured questionnaire using the RHoMIS Toolkit core modules. The RHoMIS toolkit, a Rural Household Multiple Indicator Survey, has been developed at the farm household level to assess and understand rural livelihoods. RHoMIS includes a farm household survey that can be conducted on a digital platform using tablets or mobile phones with the Open Data Kit (ODK) software adapted to Android-based mobile phones or tablets (Hartung et al., 2010; Hammond et al., 2017). The survey is a structured questionnaire that provides comprehensive information on standardized performance indicators concerning agricultural production, nutrition, food, and poverty. In total, the survey is structured in eight modules that address the specific components of the household activities and living conditions (see the modules in **Table 1**). The calculated indicators from the raw data make it possible to characterize and analyse the vulnerability of rural households while considering indicators concerning the conservation of the environment (Hammond et al., 2017).

TABLE 1 | Structure and contents of the RHoMIS questionnaire used in Morocco.

Module	Type of information	Analysiscategory
1.Household characterization	1) Head(s) of household characteristics (age, level of education, etc) 2) Household composition (members of household, their age, gender, level of education etc.).	Human capacities
2. Information on the cropping system	1) Land availability and land ownership 2) Crop management (crops cultivated, inputs used etc.) 3) Crop marketing (annual sales, self-consumption, proportion used for animal feed, etc.) 4) Resource management (water use and practices, soil erosion, soil fertility management)	Farm crop management and marketing
3. Information on the livestock system	1) Livestock ownership and composition (animal species, heads etc.) 2) Forage management by livestock type and physiological stage 3) Livestock management in terms of feed system (by differentiating feeding system in and out-door), health care, and value production (milk, meat, manure, etc.) 4) Livestock marketing (annual sales, self-consumption, a proportion used for animal feed, etc.)	Livestock management and marketing
4. Natural resources	1) Use of natural resources, especially plants, fruits, etc., in the household food system.	Biodiversity and self-sufficiency
5. Food security	1) Dietary intake in terms of diversity and food availability 2) Dietary changes throughout the year	Food (in)security
6. Aid received and debts	1) Gifts, aids,and donations (given and received) 2) Loans and debts	Appreciation of the capacity to mobilize social resources
7. Off-farm income	1) External sources of income and the nature of this income 2) Use of off-farm income	Off-farm diversification
8. Progress Out of Poverty Index	1) Based on national standard indicators of poverty	Livelihood outcomes

We can question the use of RHoMIS compared to other data collection systems or compare the livelihood outcome indicator to other livelihood measurements. However, our main objective here was more to develop and adapt the RHoMIS survey toolkit to pastoral and agropastoral systems than compare different data collection systems such as LSMS (Living Standards Measurement Study), MICS (Multiple Indicator Cluster Surveys) or DHS (Demographic and health Survey) mainly focused on wealth indicators at the household level but not necessarily focusing on rural areas. Moreover, compared to these different data collection systems, RHoMIS proposes a light data collection system focusing on household farm system highlighting the diversity of farm and off farm activity in the livelihood conditions. Additionally, one of the main goals that supports this toolkit development is to have a standard tool that can be deployed on a large scale to constitute a database according to standardized criteria and thus facilitate comparison between different areas in the context of development actions (van Wijk et al., 2020). A data quality comparison with other survey tools, amongst which LSMS (World Bank, 2017) or IMPACTlite (Rufino et al., 2013) resulted in highly credible reliable core variables and derived indicators even if some improvements are always on-going (Fraval et al., 2019).

Particularly, in the present study, one of our aims was to develop and test a new version of the RHoMIS survey by developing and implementing a detailed livestock management approach by animal species applicable to dryland areas. We also wanted to explore and better understand the diverse contribution of each animal species through its management to well-being (in terms of income) and security (in terms of assets). As a result, a set of questions were included related to the structure of the herd by physiological stage, thus providing greater insight on the main objectives of the breeder. For example, when the herd was mainly composed of young male animals, we assumed that the breeding objective was to generate added value through livestock sales to market, with or without a fattening practice. On the other hand, when the herd comprised most adult females, this was assumed to be an indicator of the reproduction capacity in the face of a shock (like a severe drought or disease which results in a significant loss of the herd). Another set of questions were related to the animal transactions (entries and exit in the flock) to assess the monetary or non-monetary generated values from animal activities. Non-monetary transactions included all social flows of animals during family (birth, marriage) or community events (alliance, compensation, solidarity).

An additional component included in the survey concerned the approach of the sociotechnical management of animals to be able to assess the productivity and the net income of livestock activity. Notably, this section provided greater detail on herd management related to each animal species to describe the practices of indoor livestock management, the period and modalities of grazing management and mobility, and the supplemental feed practices for indoor or grazing herd-models. With this approach to herd-mobility management, it was possible to assess different variables related to individual or collective herd-mobility, the keeping modality, and the breeder's mobility capacity (in terms of distance) as part of the livelihood strategy (Amsidder et al., 2021). Additional questions were related to water management and animal watering regarding period and quantity and their relative costs.

Finally, we included an economic valuation for each type of animal product (milk, hides and skin, wool, or indirect income from tourism or leisure) and whether it was consumed by the household or sold to the market. An overview of the contents of the household farm survey is presented in **Table 1**.

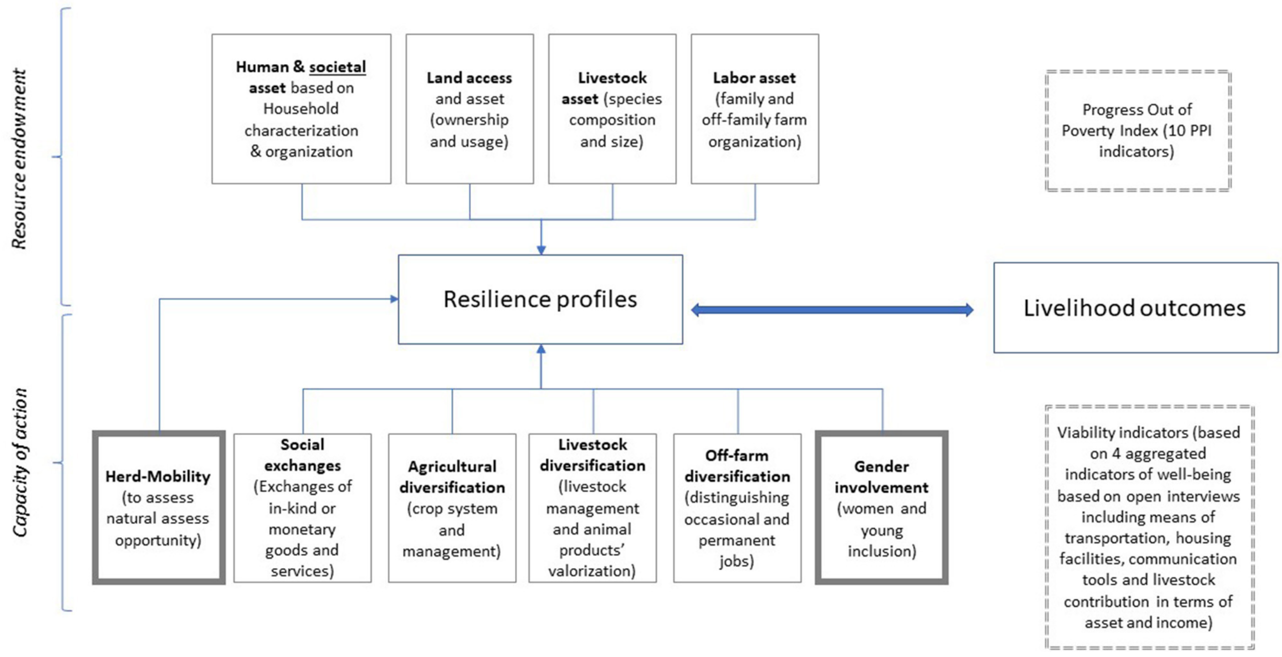

FIGURE 2 | Framework for analyzing the resilience profiles.

Components of Resilience (Adaptive Capacity Indicators)

Many studies assessing "sustainable livelihoods" at farm or household level refer to the sustainable livelihood framework conceptualized by Chambers and Conway (1991), combining capacity of action (Gondard-Delcroix and Rousseau, 2004) with stocks of assets (Lallau and Thibaut, 2009). Capacity of action is also embedded in the concepts of buffer, adaptive and transformative capacity described by Darnhofer (2014). In the current study, we took a similar approach by combining stocks of assets with capacity of action to create a set of 10 socio-economic components of resilience (**Figure 2**, **Table 2**) related to physical and human endowments, capacity of action concerning crop diversification, livestock diversification, off-farm activities, and social management at the household and community level (see **Supplementary Material 1** with the list of indicators).

Human labor, land, and livestock assets (resource endowment) were calculated based on usual asset variables related to each of these components as used in other studies (**Supplementary Material 1**). In pastoral and agropastoral contexts, the fifth set of bundles is grazing land access which depends on social network diversification, the natural ecosystem, and the formal and informal system of right and use. In our framework, this component was derived based on one main hypothesis that herd mobility management and its place in the functioning of the farm reflected the flexibility and, therefore the resilience of households when exposed to shocks, in particular in a harsh environment such as desert or mountainous areas where rainfall shortage constitutes a permanent and erratic risk (as also described in Davies and Nori, 2008; Nori, 2019).

The evaluation of crop, livestock and off farm diversification aimed to assess the capacity of action of households. For crop diversification, we selected variables related to cropland allocation, the relative use of inputs (such as chemical fertilizer and pesticides) and their on-or off-farm valorisation. Livestock diversification was evaluated based on the diversity of feed management in relation to herd mobility, and livestock products and co-products' multiple outcomes (mainly milk, meat and racing for camels) and their destinations (home-consumption or market). Off-farm diversification was a function of the nature of the contracts for the off-farm activity (seasonal or permanent).

In our framework, we proposed to include two distinct dimensions of capacity of action, i.e., "social exchanges," and "gender involvement". The "social exchanges" component was based on variables related to the social and financial exchanges of gifts, donations, or debts/loans. We assumed that the capacity to benefit from or give gifts or loans, reflects the place of the individual and his/her family in the community providing an appreciation of the social cohesion of the household, a *"critical element in social stability and economic welfare"* [as demonstrated by Narayan (1999)]. Moreover, this component attempts to reflect the diversity of functioning of the social exchanges by considering the gifts, donations and loan exchanges that can be in-kind or monetary value. In addition, we included a gender component to our set of resilience components in terms of capacity of actions. In this way, we assumed that the involvement of women or young people in the decision or accumulation (through entitlement) processes reinforces the overall capacity of action at the household level through diversification and enhancement of human capacity and social capital.

TABLE 2 | Presentation of the main socio-economic components and list of indicators to describe adaptive capacity.

Component of socio-economic resilience	Indicator extracted from the RHoMIS survey	Type of variable
Human capacity	Household characteristics such as household size, age, and level of education of the head of the household	Active
Labor asset	Family size, hired labor, exchange of labor	Active
Land asset	Land tenure, land cultivated, land fragmentation	Active
Livestock asset	Herd size by animal species	Active
Agricultural diversification	Crop diversification; crop management (fertilization, pesticide use, etc.) and crop destination (self-consumption, animal feed, or marketing)	Supplemental
Livestock diversification	Feed production, livestock products and by-products (milk, meat, racing, touristic activity) and their destination	Supplemental
Off farm diversification	Type of non-farm activities (occasional or permanent) and monetary contribution;	Supplemental
Social capital	Exchange of gift (receive or give), donations, or loans in the formal or informal institutions;	Supplemental
Mobility	Herd mobility management (individual or collective; use external shepherd; the distance of grazing land from the settlement/village; etc.) in link with social constraints/facilities and natural resources opportunity	Supplemental
Gender involvement	Women and young inclusion in the decision and action processes at the farm and off farm level;	Supplemental

Livelihood Outcomes Assessment

In a first step, in order to understand the relationship between the resilience components and overall livelihood outcomes, we needed to approach an indicator of well-being to reflect the livelihood outcome. Well-being is a broad concept that encompasses a global judgment of satisfaction with life, including fulfillment of living conditions (e.g., housing, employment) but also contentment (like happiness or positive mood) (Diener et al., 2009). In this present work, well-being is approached in terms of contentment of living conditions based on the satisfaction of material life to compared with national standards. For that, we proposed to compare two aggregated indicators of "well-being." The first aggregated indicator was composed of the ten Progress Out of Poverty Index (PPI—www.povertyindex.org) criteria defined at national level, and which estimate the probability of poverty at the 95% level of probability (Schreiner, 2007). This aggregated indicator enables the comparison of the overall poverty level in pastoral and agropastoral populations with the national population. The second indicator, that we have called "Viability," is composed of 4 sub-aggregated indicators addressing respectively, means of transportation (composed of the bicycle, the motorbike, car and the 4 × 4 car), housing facilities (tent or/and concrete), communications tools (including a smartphone), and a set of criteria related to net livestock income (animal assets and total net income per member of the family engaged full-time on-farm activities). These four sub-aggregated indicators were developed based on open interviews with key local informants (*cheikhs*–namely local authorities) and farmers. These open interviews aimed to identify the criteria that people used to classify a person or household as economically fragile or comfortable. For instance, local stakeholders and farmers used to categorize each other according to the type and age of car owned, the use of a smartphone as a means to be connected to WhatsApp groups, access to water, the housing material (including the tent), and herd-composition and size (see **Supplementary Material 1**).

In the second step, consistent with our sampling approach that focused on the analysis of the diversity of farming systems, we developed a household farm systems' typology, using a multiple correspondence analysis (MCA) on household asset variables and variables related to livelihood diversification and social management combined with the Ward method of hierarchical clustering (Ward, 1963) in each study site (respectively, in Guelmim and Tinghir). This factorial analysis technique is a descriptive approach that has the added advantage to be relevant with small sample. In our research, this set of methods was more applicable than econometric analysis that requires a large sample. The input variables comprised the set of resilience components (**Table 2**), transformed into discrete variables, combined with household assets as active variables (**Table 2**, col3), and diversification and social management as supplemental variables (see **Supplementary Material 1**). The adaptive capacity variables were transformed into discrete variables to capture their link to the function of resilience. They were transformed by the minimum score of 0 or 1, indicating a null or lower value on the adaptive capacity contribution to a maximum score of 5. However, the scoring system's number varies between their amplitude and variability related to the variability in each location of our case study. The hierarchical clustering analysis identified three types of farm households in Guelmim and four types in Tinghir. To better understand and characterize the differences in livelihood characteristics among these household types, we calculated the means for different household characteristics including household demographics, off-farm diversification, access to land, livestock herd composition and structure, and livestock production for each household type.

In the third step, we tried to understand the links between "capacity of actions" and "resource endowment" and the two livelihood outcome indicators based on "PPI" and "Viability." For that, we developed a profile of resilience for each household type. To do this, for each resilience component, we first calculated the sum of the highest scores of each variable in the component for each study site, giving the maximum contribution for each component in the studied population. We then estimated the relative aggregated score of each component for each household by calculating the ratio of the sum of individual scores over the maximum potential contribution of the component in the studied population. To generate resilience profiles, we then calculated the mean component score by household type. The same formula was applied to the livelihood outcome indicators "PPI" and "Viability," enabling us to compare the resilience components with the level of living conditions and economic viability (PPI and viability).

In the last step, we tested and validated the sets of parameters selected in each component of the resilience profiles and analyzed the correlation with the two indicators of livelihood outcome, i.e. PPI and Viability. To achieve this, we performed a multiple factorial analysis (MFA) with the variables of the 10 components of resilience as active variables and the variables of the two components of livelihood outcomes (PPI and Viability) as supplemental variables.

RESULTS

Characterization of Livestock Household Farm Systems' Types

The main characteristics of the agropastoral and pastoral systems issued from two clustering analyses on the first factorial axis of the multiple correspondence analysis conducted in the two zones (descriptive statistics are given in **Supplementary Material 2**) are presented in **Figure 3**.

In Guelmim, we used the two first factors representing 17% of the variance of the sample. The first axis differentiated the large and specialized camel-based system (called "G3") and the diversified camel-system withcrop production (called "G1"). The second axis allowed the identification of a third group ("G2") representing the traditional agropastoral systems based on camel and small ruminants (sheep and goats). Group (G3) gathered the youngest family leaders who have developed a specialized camel-based system. In this group, family heads diversify their source of income by valorizing different camel activities, such as camel racing through the regional festivals and milk products, in addition to the sale of live animals. The second group (G2) corresponded to traditional agropastoral systems where camel-herds move with a large flock of small ruminants (around 350–400 animals), composed of two-third of sheep and one-third of goats. Finally, (G1) comprised the smallest camel-herd that grazed on communal land. This group benefited from communal land where they were able to grow, in rainy years, wheat for home consumption and barley for animals.

In Tinghir, the clustering analysis was performed on the coordinates of the individuals on the three first factors representing 33.6% of the variance. The first factor isolated group T2, representing the specialized pastoral system based on permanent grazing practices of a large flock (around 600 sheep and goats). Contrary to the others groups, this group (T2), mainly localized at higher altitude, and has not developed any crop activity. Factor 2 differentiated the diversified agropastoral systems according to the flock size, separating the group (T1) and (T3). The group (T1) comprised the extensive agropastoral system that kept around 400–450 animals. This group also owned the largest land area (around 6 ha) used to cultivate cereal or fodder crops. At the opposite side, group (T3) owned less than 100 sheep and goats, with most goats, on <1.8 ha of cultivated land. However, contrary to the last group (T4), the farmers in (T3) had developed a cattle activity (with around eight cattle). Finally, the last group (T4), was characterized by owning about 180–200 heads but without a cattle activity.

Resilience Profiles and Livelihood Outcomes

Based on this categorization of the agropastoral and pastoral systems, we generated the aggregated scores of each resilience component to assessthe associations with the livelihood outcome indicators based on "PPI" or the proposed aggregated indicator "Viability," composed of the criteria identified during our open interviews with the key stakeholders. **Figure 4** presents the profiles of each system, respectively, for the camel-based systems in Guelmim (A) and sheep and goats-based systems in Tinghir (B).

Figure 4 reveals that livestock assets (Livestock_Tlu) differentiate the livestock farm systems' types in both study areas, but to a lower degree in Guelmim. However, we can observe that the large pastoral and agropastoral systems in both regions have both the maximum stock of animal assets. Another striking finding is that we observe contrasting variability in the spider diagrams between the two studied zones. Although the three camel-based systems in Guelmim present relatively similar profiles in terms of the combination of assets and capacity of action, we see more significant differences in the resilience profiles in the sheep and goats-based systems in Tinghir. Notably, in the sheep-goats-based systems, land asset and crop diversification are higher in the agropastoral systems than in mixed small-scale crop-livestock systems. This differentiation of land and crop-based systems reflects the differential capacity of investment allowed by a large flock. Besides, we can see that women and young are more involved in the specialized pastoral system than in the other mixed crop-livestock systems.

The livelihood outcome indicators also present different profiles of the resilience of the systems in Tinghir compared to Guelmim. PPI and Viability remain consistent for each household type in relation to livestock assets in arid zones in the camel-based system. However, in Tinghir, we observeddifferences between these indicators for the large agropastoral (T1) and the pastoral system (T2), which record a low score for PPI compared to Viability. On the other hand, the diversified cattle-small ruminant system (T3) recorded a higher score for PPI than Viability. The small-scale mixed crop-livestock system exhibited similar scores for the livelihood outcome variables. Furthermore, in Tinghir, while the PPI scores reveal better living conditions of the mixed crop-livestock system, Viability scores suggest that the pastoral and agropastoral systems have slightly higher resilience than the diversified crop-livestock systems. This contrasting

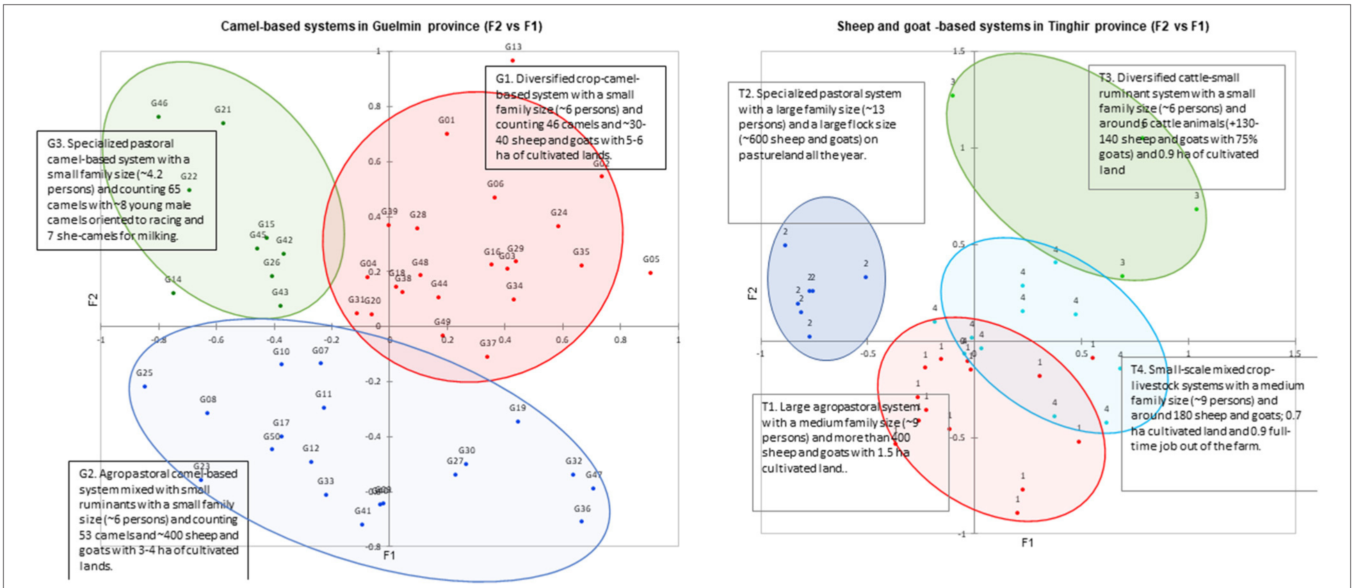

FIGURE 3 | Typology of livestock farming systems in the two studied sites (camel-based systems in Guelmim on the left and sheep and goats farming systems in Tinghir on the right)].

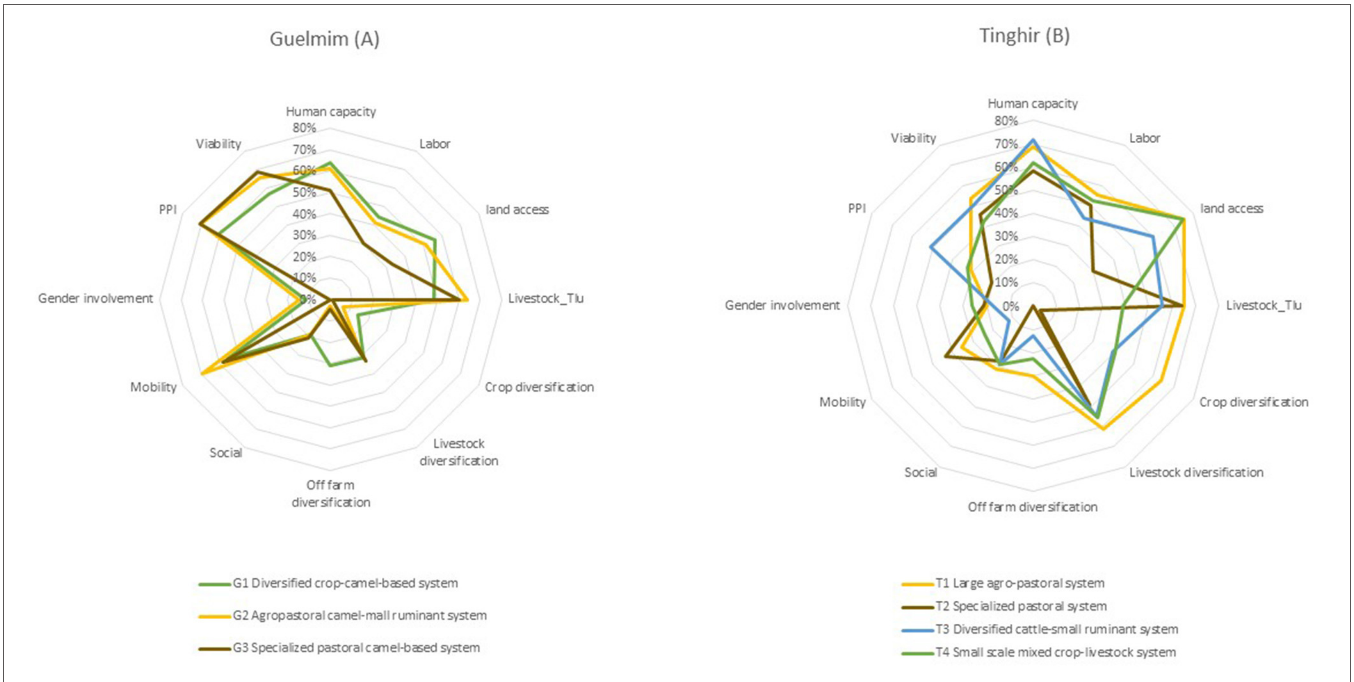

FIGURE 4 | Profiles of resilience for each agropastoral and pastoral systems by distinguishing camel-based systems in Guelmin **(A)** and sheep and goats-based systems in Tinghir **(B)** (PPI: Progress Out of Poverty Index).

difference between PPI and Viability indicators is not observed for the camel-based systems in Guelmim where the main asset and diversification strategy are based on the camel animals.

Figure 5 shows that the PPI indicator reveal greater heterogeneity between sites, while the Viability indicator reveals greater heterogeneity within sites. We can see that the two indicators PPI and Viability present the most contrasting results for the two large agropastoral systems, i.e., the diversified crop-camel- based system (G1) in Guelmim and the large agropastoral system in Tinghir. Indeed, the Viability score enables the assessment of variability within site in associationwith the multiple outcomes of animal products and co-products compared to the PPI indicators which aremainly based on land and crop diversification (see **Supplementary Material 3**).

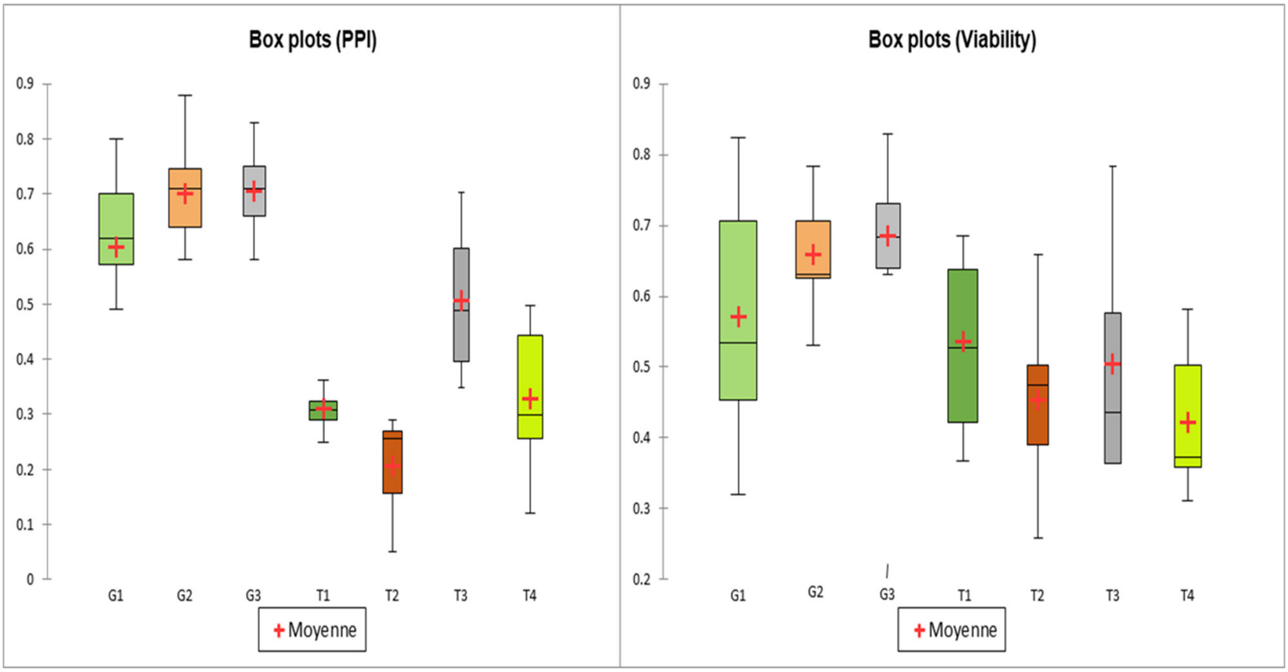

FIGURE 5 | Inter- and intra-heterogeneity of the livelihood outcome indicators for each agropastoral and pastoral systems in the two case studies. G1, Diversified crop-camel-based system; G2, Agropastoral camel-small ruminant system; G3, Specialized pastoral camel-based system; T1, Large agro-pastoral system in Tinghir; T2, Specialized pastoral system in Tinghir; T3, Diversified cattle-small ruminant system in Tinghir; T4, Small scale mixed crop-livestock system in Tinghir.

TABLE 3 | Matrix of correlation between the 10 themes and the indicators of livelihood.

	Guelmim		Tinghir		Total sample	
Variables	**W_PPI**	**W_Viability**	**W_PPI**	**W_Viability**	**W_PPI**	**W_Viability**
Human capacity	−0.022	0.017	0.100	0.095	−0.130	−0.048
Labor	−0.150	−0.037	−0.243	−0.191	**−0.452**	**−0.286**
Land access	**−0.332**	−0.021	0.282	−0.038	**−0.309**	−0.183
Livestock_Tlu	0.161	**0.441**	−0.073	**0.506**	0.052	**0.408**
Crop diversification	**−0.578**	**−0.323**	0.233	0.126	**−0.568**	**−0.364**
Livestock diversification	−0.008	0.164	−0.076	0.015	**−0.593**	**−0.285**
Off farm diversification	**−0.426**	−0.135	0.222	0.071	−0.126	−0.069
Social	−0.045	−0.178	0.113	−0.123	**−0.254**	**−0.286**
Mobility	**0.321**	−0.154	**−0.478**	−0.040	**0.595**	**0.283**
Gender Involvement	0.122	0.145	−0.070	−0.102	**−0.251**	−0.129
PPI	**1**	**0.371**	**1**	0.197	**1**	**0.543**
NetInc_per_TLU_code	−0.142	**0.398**	0.143	**0.705**	−0.081	**0.411**
NetInc_per_FFT_code	0.214	**0.787**	0.050	**0.902**	**0.249**	**0.809**
NetInc_per_poverty_level	0.237	**0.802**	−0.019	**0.852**	**0.247**	**0.808**
Total_poverty _perc_class	**0.931**	0.276	**0.946**	0.116	**0.933**	**0.437**

Values in bold are different from 0 at a significance level alpha = 0.05.

Disaggregated Approach of the Resilience Based on the Resource Endowment and Capacity of Action

To analyse the proximity between the livelihood outcome indicators and the capacity, we implemented a multiple factorial analysis conducted on the 10 components of the resilience profiles and including the two livelihood outcome indicators as supplemental variables. **Table 3** presents the correlation matrix between the different scores for each component of the resilience profile representing the resource endowment and capacities of action with the two proposed indicators of livelihood outcomes.

A significant association was observed between PPI and Viability indicators, with a multivariate correlation coefficient (RV of 0.389). However, these two components of the livelihood approach differed slightly in regard to the profiles of stock of assets and capacity of action. On the one hand, the PPI component is relatively more associated with human capacity, crop diversification, and women or youth involvement in decision and control management than the "Viability." On the other hand, the "Viability" component is more associated to the "Mobility" and "Livestock-Tlu" components. Surprisingly, the stock of land and, to a lesser degree, labor organization have a more distant relationship with the two livelihood outcome indicators. In contrast, land access seems to be a more robust differentiating variable in the typology. The overall correlation between the components of the resilience profiles and the two livelihood outcome variables is slightly higher with PPI (RV = 0.549) than Viability (RV = 0.438).

The matrix reveals also similarities in labor organization and crop and livestock diversification. The main differences in the correlations of each component with livelihood outcomes occur with the stock of assets components of the resilience profile. While there is a significant correlation between PPI and stock of land assets, this correlation is not significant with "Viability." Furthermore, we observe the opposite pattern with the inventory of livestock assets, with a positive and significant correlation with "Viability."

DISCUSSION

Heterogeneity and Convergence in the Agropastoral and Pastoral Systems of South-Eastern Morocco

It was notable that the resilience profiles of the farming household types were largely similar within each study site (**Figure 4**), indicating that the variability between sites was much greater than the variability found within sites. Given the contrasting agroecological and socio-economic contexts of these two rural agropastoral and pastoral systems of southand eastern Morocco, this may have been what one expected. However, a number of studies on mixed crop-livestock systems suggest that household variations in asset holdings often outweigh larger-scale geographic, socio-cultural, and economic differences (Ellis and Bahiigwa, 2003; Ellis and Freeman, 2004; Tittonell et al., 2005). Our results on the other hand align with other studies more focused on agropastoral and pastoral systems that emphasize the effect of location specific factors in determining resilience (Abebe, 2020; Melketo et al., 2021). As a number of such studies indicate, context-specific factors such as climate, disaster-risk proneness, distance to market, access to irrigation, access to credit, local politics among others are important determinants of household resilience(Perez et al., 2015; Bera et al., 2020). These contrasting results between livestock or crop-oriented systems may indicate important differences in factors affecting overall household resilience.

Taking a closer look at the differences in the resilience profiles between sites, the major differences tended to be associated with livelihood diversification [off-farm diversification, livestock diversification, and crop diversification, considered in the capacities of action in our frame (**Figure 2**)], where household types from Tinghir were more diversified than the household types from Guelmim (**Figure 4**). Moreover, within site, the variability in livelihood diversification was greater in Tinghir compared to Guelmim, with household type of specialized pastoral systems in Tinghir (T2) displaying much lower levels of diversification in terms of off-farm diversification or crop-diversification compared to the other household types in Tinghir. These differences between and within sites in livelihood diversification are especially important as livelihood diversification is often identified as a key strategy in building household resilience (Wu et al., 2014; Martin and Lorenzen, 2016; Sarker et al., 2020).

One of the main reasons for the differences in livelihood diversification between sites is likely a result of the overall vulnerability of the households of the two sites. As observed in the livelihood outcome variables (PPI and Viability—**Figures 4**, **5**), households from Guelmim are much less prone to poverty and their livelihood strategies are much more viable than the households from Tinghir. While livelihood strategies with no doubt contribute to livelihood outcomes, there is also an important iterative process or bi-directional dependence between resilience profiles and livelihood outcomessuch that livelihood outcomes will also influence the livelihood strategies employed by the farming households (**Figure 2**). In this sense, the farming households of Tinghir are compelled toward livelihood diversification strategies in order to build resilience in the face of higher levels of poverty and lower levels of livelihood viability, placing them in positions of greater vulnerability. This finding closely reflects the conclusions of a recent study investigating livelihood diversification in a riverine context in rural Bangladesh. In this study it was shown that resource poor households tended to exhibit greater livelihood diversification than resource richer households (Sarker et al., 2020).

On the other hand, the comparatively improved livelihood outcomes of the farming households in Guelmim coupled with the economic opportunities presented by an easily accessible urban center nearby are key factors that may enable these households to thrive by adopting more specialized, less diverse, livelihood strategies. The most extreme example of this is with the specialized pastoral camel-based systems(G3) that specialized in pastoral camel systems generating significant proportions of their income through niche activities related to camel racing (see **Supplementary Material 2**). This finding reflects the conclusions from a study in Botswana, where, when the conditions were conducive, wealthier and more powerful households often employed "accumulator" livelihood strategies specializing in the rearing of livestock (Sallu et al., 2010). Besides, we need to mention that the Guelmim-Oued Noun region, at the gate to the Sahara, has also benefitted from significant support, especially from the state. This support has followed the Sahara conflict which had implied important investments in terms of infrastructure (mainly roads) and a settlement of civilians as well as military troops. This situation differs significantly from Tinghir, which is not an important trade route. However, the two areas always receive barley grains at a subsidized price that were considered into the net income calculation.

With regard to the greater variability in livelihood diversification within Tinghir, it appears that these differences may be driven by access to land. Specifically, as noted above, T2 farming households differed from the other household types in Tinghir as their crop and off-farm diversification levels were much lower. It is likely that the lack of livelihood diversification among these households was a result of lower levels in land access, the other resilience component that displayed important differences among household types in Tinghir (**Figure 4**). Leading a fully pastoral lifestyle without owning or cultivating land prevents livelihood diversification into crops. Furthermore, it is likely that a full mobile pastoral lifestyle is also very labor intensive as indicated by the number of males and females in the household active on-farm (**Supplementary Material 2**). This is confirmed by the particular profile of gender involvement for T2. Women and young are strongly involved in mobility management throughout the year. This also prevents livelihood diversification through off-farm income generating activities as more members of the family are employed on-farm.

Although many studies in pastoral areas have highlighted the role of livestock as social capital (Thébaud and Batterbury, 2001; McCarthy and Di Gregorio, 2007; Moritz, 2008), **Figure 4** displays weak variation of the social exchanges in association with the different profiles of resilience. Indeed, our results tended to display a negative correlation between social exchanges and livelihood outcomes indicators. In fact, the social exchanges in terms of loans or gifts in kind or money are more developed in the less resilience population. However, we cannot omit that the present approach does not reflect the real exchanges of live animals that have been difficult to capture in our survey.

These mobile, but landless, households therefore face significant structural barriers to livelihood diversification due to their inability to exploit opportunities for further income generation either through crop production or off-farm activities. Without these pathways to building resilience, it is likely that they will remain particularly vulnerable compared to the other farming households in the area. As such, our results support other research that suggest pastoral systems in Morocco will face even greater existential threats in the coming decades due to a variety of environmental (e.g., climate and land-degradation) and socio-economic (e.g., land-use change and household characteristics) factors (Martin et al., 2016; Schilling et al., 2020). Indeed, as a recent study has shown these threats are leading to a consistent trend toward the conversion of pastoral land to agricultural land in southeast Morocco (Lamqadem et al., 2019). Greater investment in long-term management of rangelands and pastoral livelihood security is therefore key to supporting these farming households (Martin et al., 2016).

Indicators of Livelihood Outcomes and Perspectives

The comparative analysis of household resilience and livelihood outcomes for the different identified livestock farming systems in Morocco based on herd-mobility revealed the different roles of each animal species in their contribution to the overall resilience profiles and, consequently, their impact on the livelihood outcome indicators. In Guelmim, we noted large similarities between PPI and Viability indicators in line with animal stocks, mainly defined by camel assets. Conversely, the relations between animal stock and livelihoods outcome indicators present different configurations in the sheep and goat-based systems according to the complementary role of crop and off-farm activities, family size, and how to conceive the livelihood measurement. As soon as the system is based on large ruminants like cattle in the "diversified cattle-small ruminant system in Tinghir" (T3), we note similar profiles for PPI and Viability livelihood indicators. The similarity of livestock conditions is also observed for the small-scale mixed crop-livestock system (T4) with a relatively good land basis compared to the other types in the sample. On the other hand, we note significant differences between PPI and Viability indicators regarding the pastoral and agropastoral systems based on sheep and goats. The "Viability" indicator better reflects the capital related to animal stock and animal diversification outcome. So, this result questions the use of the PPI indicator as a livelihood measurement in the pastoral systems based on small ruminants.

Understanding this contrasting result between systems oriented to large ruminants or small ruminants is explained by the different roles played by animal species in the overall livelihood outcomes (Alary et al., 2011, 2015). Linking these results with the framework proposed in Darnhofer (2014) who highlights three aspects covered by resilience, i.e., buffer capability, adaptive capability and transformative capability, this analysis highlights the larger contribution of camels and cattle in terms of transformative capacity of the household system, contrary to sheep and goats that can generate important monetary fluxes but not necessarily physical accumulation (either for housing or farming). As such we can argue that sheep and goats increase the "buffer" and even "adaptive" capacity of rural households in case of shocks, but not necessarily their "transformative" capacity. Here the buffer and adaptive capacities refer to the concept of farm resilience developed by Milestad and Darnhofer (2003) and used in different research works (e.g., Speranza, 2013).

In parallel, the interviews with key stakeholders in each area allowed us to get an insight into some common perceptions about the livelihoods of the different farm groups based on herd size. For instance, in Guelmim, families can rapidly have an idea about the living conditions of each other based on camel-herd and sheep-goats flock size. According to a number of interviewees, a family with more than 50 heads of camel, lives well. Below this threshold, "*it will depend on the sheep and goats flock size...with 200 sheep and goats, a family can achieve similar living conditions to families with more than 50 camels*" (declaration). These explanations align closely with the household types that were defined through the MCA and the corresponding livelihood outcome indicators (PPI and Viability). Group (G3) comprised the farmers with more than 50 camels, while groups G1 and G2 represented the households with or without the complement sheep and goats flock. In Tinghir, the discussions conducted with key stakeholders highlighted the contrasting living situations between the pastoral systems in the mountainous zones from the agropastoral or mixed systems along the Dadès valley. The typology reflected these distinctions too, clearly defining the transition from pastoral to integrated crop-livestock systems along the valley. The livelihood outcomes indicators put in exergue different capacities, i.e., the capacity of action for mixed systems through the PPI and the resource endowment for large pastoral systems through the Viability score. We can note that the "Viability" score through a set of performance indicators related to income address the monetary poverty (see **Supplementary Material 2**).

With regard to the proposed conceptual frame work outlined in **Figure 2**, we can conclude that the "PPI" livelihood outcome indicator conceived at the national level, remains a relatively good proxy of the living conditions of pastoral and agropastoral systems based on large ruminants. On the other hand, the "Viability" indicator highlights relatively well the combination of endowments and diversity described in the resilience profiles (like proposed by Chambers and Conway, 1991). This indicator considers the variety of system components and diversity of livelihood options that confer a certain degree of flexibility and then an adaptive capacity in their livelihood strategies (as also observed in Robert and Lallau, 2016).

Moreover, notwithstanding these findings, it is important to note that with our methodological approach, the transformation of the raw or calculated data into discrete variables to capture their association to resilience raises some issues. For example, the collective management of a livestock herd with different herd-owners can be either perceived as an indicator of robustness (if this enables livestock-breeders to exploita larger territory in relation to a social network) or vulnerability when herd-owners are forced to participate in collective management due to lack of equipment or human resources to conduct mobility alone. To better understand these dynamics within the local contexts of the research areas, the research teams used the formal and informal interviews that were conducted with community elders and local key stakeholders in the form of life stories (by referring to the approach of Vincent-Ponroy and Chevalier, 2018). However, this point raises the question whether such a variable should then be included as an indicator of resilience when attempting to develop a generic approach for the assessment of resilience profiles of pastoral and agropastoral systems? Moreover, would it be more appropriate to explore the underlying drivers, i.e., access to equipment and human resources? However, it is well recognized that the approach focusing on drivers does not solve the problem completely, especially from the perspective of using collective management as a form of generating greater resilience. Collective management seems to be both a product of vulnerability and an opportunity to achieve greater access to land. As such we argue that this approach requires a context-specific scoring system for some indicators. Only the set of proposed indicators constitute a sound basis to approach the diversity of livelihood strategies of pastoral and agro-pastoral systems. This list of proposed indicators is currently analyzed in front of a diversity of (agro) pastoral systems through an expert group working in North and Sub-Saharan African countries. Another step will be to compare livelihood outcomes indicators with other livelihood measurements as discussed by Alkire (2002), Ramos and Solber (2005) or by McPeak et al. (2011) for (agro) pastoral households. The presented development of data collection and research on composite indicators to capture livelihood status in pastoral systems highlights the need to work more on clusters of indicators rather than a single indicator of livelihood outcome in these systems, considering the multiple and variable functions of animal species. Finally, as also mentioned in McPeak et al. (2011), capturing the direct and indirect flows from the social and economic transactions around livestock activities such as gifts and transfers also remains a challenge.

CONCLUSION AND PERSPECTIVES

The results clearly show that understanding the multiple functions of livestock assets as well as the heterogeneity of the production systems of breeders and their families constitutes a first and unmissable step in the elaboration of compatible development options to improve the livelihood conditions of pastoral and agropastoral systems living in these arid and uncultivable areas.The proposed framework allowed us to capture the bi-directional dependence between resilience profiles and livelihood outcomes. Notably, our case study highlighted the fact that livelihood outcomes are both a product and a determinant of resilience profiles. This holistic approach based on factorial analysis also highlighted the structural barriers to livelihood diversification of some pastoral and agropastoral systems. These barriers are related tothe degree of ability to exploit opportunities for further income generation either through crop production or off-farm activities. Furthermore, this ability is also conditioned by livestock composition and, consequently, the potential accumulation process in and out of agriculture. However, one of the main bases of this dynamic is firmly embedded in the long-term management of rangelands that condition pastoral livelihood security over time.

From a methodological point of view, our work allowed to develop an operational framework for addressing and assessing living conditions of farming household whose livelihoods depend on livestock incomes in dryland areas. This approach underlines the multiple roles that livestock can play in relation to animal assets and their management and the role of complementary activities such as crop cultivation or off-farm activities. However, this approach also highlights heterogeneities due to the context that conditions different opportunities of diversification (capacity of action), also involving different needs and development options. This context-specific factor reinforces the need to employ a solid database collection system, enabling the capture of both general and specific components of resilience profiles based on a holistic approach. In this line, RHoMIS constitutes a sound basis for data collection, allowing to some local adaptation. The new version of the livestock modules developed within this work and the performance indicators developed within this current framework presented in the paper could be an excellent basis to define resilience profiles considering the organization and functioning of household systems based on mobile livestock activity. Moreover, this approach could constitute a valuable contribution to help fill the knowledge gaps that limit policy makers in developing contextualized rural development policies and instruments in these very vulnerable environments where livelihood outcomes are mainly based on livestock asset.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by approval and consentement of the surveyed persons. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

VA, LA, JH, MV, IB, and TS contributed to conception and design of the study. XJ and AS organized the database. VA, XJ, and MC performed the statistical analysis. VA wrote the first draft of the manuscript. MC wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2021.723994/full#supplementary-material

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KAZNET: An Open-Source, Micro-Tasking Platform for Remote Locations

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Field surveys are the workhorse of social and environmental research, but conventional collection through monitors or enumerators are cost prohibitive in many remote or otherwise difficult settings, which can lead to a poor understanding of those environments and an underrepresentation of the people living in them. In such cases, micro-tasking can offer a promising alternative. By activating *in-situ* data collectors, micro-tasking avoids many of the large expenses related to conventional field survey processes. In addition to relaxing resource constraints, crowd-sourcing can be flexible and employ data quality protocols unheard-of for conventional methods. This study assesses the potential of using micro-tasking to monitor socioeconomic and environmental indicators in remote settings using a new platform called KAZNET. KAZNET leverages the network of people with smartphones, which are becoming ubiquitous even in the remote rural settings, to execute both long-term and short-term data collection activities, with flexibility to adjust or add tasks in real-time. It also allows for multiple projects, requiring different data types, to be rolled out in the same platform simultaneously. For the data-collector, KAZNET is effectively a wrapper for the commonly used and open source, Open Data Kit (ODK) software, which specializes in offline data collection. A web interface allows administrators to calibrate, deploy, and validate tasks performed by contributors. KAZNET has been used in several projects to collect data in remote pastoral regions of East Africa since its inception in 2017. KAZNET has shown to be effective for collecting high frequency and repeated measures from markets, households and rangelands in remote regions at relatively low cost compared to traditional survey methods. While the successes of micro-tasking are promising, there are clear trade-offs and complementarities between micro-tasking and standard surveys methods, which researchers and practitioners need to consider when implementing either approach.

Keywords: data collection, drylands, pastoralists, micro-tasking, open-source

INTRODUCTION

The importance of timely and accurate data cannot be overemphasized when it comes to decision making (World Bank, 2018). Whether these decisions take place in the social or environmental domains, at the household-, community-, or policy-level, decision makers require accurate information. Gathering such data is often expensive and time consuming (Bitso et al., 2020), which especially holds true in remote and difficult to reach regions. The result is that these areas are often poorly-sensed, which leads to mis-representation and sometimes oversight all together.[1] The resulting data scarcity has slowed the achievement of development goals aimed at improving the livelihoods of poor communities (Bitso et al., 2020).

Conventional field surveys are the workhorse of many environmental and social science fields that require data from outside of the lab. Primary data collection from enumerator-to-respondent surveys, focused group discussions, sensor readings, and key informant interviews collected through on-site trained data monitors or enumerators, is the norm for those working on research or development in rural settings (Nyariki, 2009). These approaches usually either involve experts collecting data directly or experts training others to collect data in the expert way, both of which can generate very accurate data but can also be extremely expensive. In addition to the large transportation, lodging, feeding, training, salary and maintenance requirements, such approaches are not flexible or dynamic, and therefore struggle to respond changing environments or dynamic data needs. Equally notable is that the large, fixed costs of launching such field campaigns can reduce the frequency of data collection even when higher frequencies are clearly preferred. And, because the campaigns are infrequent, they can represent an effectively unique opportunity for a researcher or statistics office, which can lead to larger, longer, and more expensive data collection efforts, thereby further reducing the frequency of those activities.

Micro-tasking leverages advances in digital and mobile technologies to draw on a large pool of *in-situ* data collectors. Complex data collection processes are commonly broken down into a series of smaller and less complex tasks so that contributors do not have to go through costly onboarding processes typical of conventional methods (Minet et al., 2017; Durward, 2020; Sveen et al., 2020; Van De Gevel et al., 2020). The expansion in access to, and use of, smartphones simultaneously grow the pool of data collectors available for micro-tasking, provides ICT training, provides a channel to recruit and remotely train potential contributors, and provides a platform for the micro-tasking software itself (Mtsweni and Modiba, 2020).

In any data collection activity, limited supervision can generate low quality data and micro-taskers often operate with little individual supervision (Gadiraju et al., 2015), but there are several mechanisms for improving data quality that are available to micro-tasking that are less available for conventional approaches (Neto and Santos, 2018). For example, the low cost of data collection provides a high density of observations that can be used to cross-validate data between observations and flag outliers. Further, ICT-related features, such as photo verification, geo-fencing, which only allows tasks to be completed in a specific location, temporal gates, which only allow tasks to be completed on a specific time or date, and dynamic feedback, can be easily integrated into product design. Such features reduce the risk of lower data quality that data-collectors might generate when working without on-site supervision (Robert, 2019). In addition, when these features are combined with dynamics incentives, they can be used to direct sampling, thereby addressing concerns that contributors' preferences will drive sampling and bias the resultant data (Jensen et al., 2017).

Data collection through micro-tasking offers real-time flexibility that is not possible under conventional methods (Kittur et al., 2008). For example, networks of existing contributors can be activated or deactivated, and/or new contributors brought on board in response to changing data needs. New tasks targeting different subjects can also be launched on the same platform and performed together or independently with other tasks (Kittur et al., 2008). Further, data collection forms, question, and related parameters can be adjusted and re-deployed with little effort from platform administrators. The real-time adjustments on the type and content of tasks are a particularly relevant and important feature that can be used to quickly activate information gathering in response to infrequent and acute events, such as drought or pandemic, in ways that conventional approaches could not because the of lag time associated with recruiting, training and transporting appropriate data collectors. While this feature further reduces the cost of setting up data collection, it also allows multidisciplinary approaches to projects by pooling together expertise in different subjects to use a single platform (Cuccolo et al., 2021).

One key feature of micro-tasking is that contributors continue with their daily lives, while also occasionally completing tasks when convenient. The result is that local data collectors are usually the favored because they have the least transportation time and expenses to incur, and often preferred by the project because they are likely to have local knowledge and access that can improve data quality and further reduce transaction costs (e.g., time spent locating respondents). Further, such arrangements avoid many of the costs incurred to support enumerators during conventional data collection campaigns, which are fulltime for the enumerators and therefore require food, lodging, transportation and on-site management (Edgar et al., 2016). Once the network of contributors is activated, rewards for completed tasks are the main cost incurred. Dynamic reward systems can be set up that incentivize quality and quantity. This flexibility in rewards avoids paying for, and disincentivises poor quality data. Contributors also have the freedom to perform tasks that give them maximum reward for their effort, while administrators can use a value of information framework and adjust rewards to incentivize increased or reduced collection of specific tasks to reflect the marginal value of an additional observation (Allahbakhsh et al., 2013; Jensen et al., 2017). In the case where incentives are monetary, the activity also provides the contributors with an additional source of income. Other types of rewards for participating, such as providing

[1]For very relevant examples in conflict regions and pastoral regions, see Hoogeveen and Utz (2020) and Wild et al. (2019), respectively.

contributors with access to processed data, can also further reduce costs and increase access to information by contributors in ways that conventional survey methods rarely do (Chelanga et al., 2021).

Despite the overarching benefits and extensive use in many fields, there are mixed views on the value of micro-tasking (Liu, 2017; Phuttharak and Loke, 2018). Critics argue that the data generated through micro-tasking has more errors and is more likely to be biased than data collected by scientists, technicians, or enumerators, using conventional instruments. However, proponents of micro-tasking argue that projects using non-expert contributors continue to produce high-quality data, equivalent to and sometimes surpassing trained enumerators (Eklund et al., 2019). Other scholars and practitioners argue that each dataset generated through micro-tasking should be judged individually, based on the context in which the project is implemented, as it could strongly complement traditional methods (Uhlmann et al., 2019).

In this study, we investigate the potential for using micro-tasking to monitor environmental and socio-economic indicators in remote and underrepresented pastoral regions in Africa, one of the most challenging contexts for data collection. To this end, we first present a phone-based micro-tasking platform named KAZNET that was explicitly developed in and for the extensive pastoral systems of the Horn of Africa, where credible data on household nutrition, rangeland conditions, market prices, consumer product availability and quality, disease outbreaks, conflict, forage availability, and other welfare and environmental indicators are dearly lacking (Tollens, 2006; Meena and Singh, 2013). Importantly, KAZNET was developed to suit the pastoral context, both in its user-interface that pastoralists use to browse, select, and complete tasks and its offline capabilities, which are unique in the micro-tasking field but necessary for this environment. We then provide several examples of high-frequency data collected with KANZET and discuss them in terms of quality and potential value for long-term high-frequency monitoring. Finally, we discuss ongoing research on improving the long-term sustainability of the platform, with notable advances in dynamic task allocation, reward optimization, and engagement with the private sector.

The remainder of this manuscript is organized as follows: the next section provides more details on the platform and its development; this is followed by a section on results which demonstrates KAZNET's functionality and value through a series of three applications. The Discussion section closes the manuscript, highlighting the platform's scalability and limitations.

METHODS

The KAZNET platform was designed to operate as a micro-tasking platform to be used by pastoralists in rural and remote locations. Its origins lie in the demand for lower-cost options for collecting structured and high-quality data from remote regions by the International Livestock Research Institute (ILRI) research team. This demand led to a search for existing viable alternatives to the standard survey approaches that the team was using at the time, which resulted in a review of the literature and multiple discussions with ICT-for-development experts. The efforts revealed that, while crowdsourcing approaches might meet the objective, there were few micro-tasking or crowdsourcing platforms targeting the agricultural sector and those that existed all focused on crop farming. There were no platforms developed specifically for pastoral systems or even with pastoral systems in mind. Importantly, none of the platforms functioned offline, making them effectively unusable in most pastoral settings.

While the review did not offer an existing solution, it did inform the design and strategy for a scoping mission focused on assessing the potential for micro-tasking in dryland pastoral settings. The scoping mission took place in 2016 with the objective of assessing the demand for improved data from and to the dryland pastoral settings and the infrastructure available for ICT-based solutions to meet that demand. It was carried out across different sectors operating in the drylands, including the private sector, international development organizations, government institutions, and pastoralists.[2] The study showed that there was high and unmet demand in the public and private sectors for a reliable system that could collect and disseminate relevant information at high-frequency and low-cost. Further, smartphone penetration was observed to be high and seemingly offered an opportunity for micro-tasking or citizen science approaches to data collection.[3]

While the types of information demanded varied across stakeholders in correspondence to their diverse areas of operation, the need for improved livestock market information was identified by multiple stakeholders. A second scoping mission, this time specifically targeting livestock market information, was undertaken in 2017. The objective of this activity was to develop and pilot the tasking process to be used in remote livestock markets. The results of this second scoping mission and literature on incentive infrastructure used in other micro-tasking platforms reinforced the need for flexibility in the platform.

In 2017, ILRI engaged Ona, a software engineering firm located in Kenya, with a background that includes, among other products, developing Ona Data, a mobile data collection platform based on Open Data Kit (ODK). ODK is an open-source survey software that was developed to function in no/low bandwidth environments—thereby meeting our first requirement of functioning off-line. Because ODK, and Ona's version of it, were developed to make it easy for researchers to develop, launch, and update surveys with little or no coding experience, it met our second requirement—flexibility—in that users can easily adjust or change survey tools in near-real-time. Ona has gone on to develop the entire KAZNET platform, which is completely open source and relies on the same tool-building approaches that all ODK users will be familiar with.

[2]While it was clear that there was great demand at ILRI for improved data from these regions, the feasibility study focused on demand for data by other stakeholders in the region.
[3]See Gesare et al. (2017) for more details on the scoping mission and its findings.

Micro-Tasking Platform Process

The KAZNET platform consists of two main components: a web application, and a mobile application. The web application is used by the administrators of the platform to design and manage tasks, approve or reject submitted tasks, calculate payments, and access the submitted data. The mobile application provides contributors with a menu of available tasks, with descriptions of parameters and filtering options for geofences and temporal gates. It allows the registered contributors to download tasks for completion offline, perform tasks, submit tasks, and receive feedback on the quality of their submissions (e.g., the reason that a task was rejected).

Figure 1 demonstrates the sequence of actions between an identified demand for data and the delivery of that data. A detailed description of the two components follows.

Web Application

The KAZNET web application is custom built by Ona to provide an interface for developing, deploying, managing, and approving tasks. In the current deployment, tasks are defined as an ODK form with a related set of parameters that define protocols. Task development then includes two steps—authoring forms and defining parameters. In our case, forms are authored using the Ona Data platform, but other platforms (e.g., Kobo Collect, Survey CTO, ODK Cloud) could feasibly be linked to the KAZENT web application. Importantly, all the standard features of ODK forms are available for the form development, including question types, time stamps, geo-stamps, photo capture, video/audio playback, skip logic/branching, as well as application features such as remote updating of forms. The task's parameters are then defined within the KAZNET web application. The parameters include (1) where the task can be completed—the geofence[4]—if there are restrictions, (2) when tasks can be completed—the temporal gate[5]—if needed, (3) the maximum frequency that the task can be completed, (4) the qualification requirements of the task, and (5) the reward for accepted task completions. The task is then defined as the ODK form and the set of parameters. Administrators can also provide a set of auxiliary instructions to the contributor. **Figure 2** includes a screen shot of the web page used to parameterize a task. Note that parameters and notes are communicated to the contributor through their mobile application, which we discuss below.

Contributors are registered, allocated login credentials, and progressively categorized by performance and experience. Those with sufficient experience and consistently high performance (experts) could have access to some tasks that are deemed too challenging or sensitive for unproven beginners. Rewards are set to reflect the data needs and the complexity of the tasks—tasks requiring more effort are priced higher than those that require less effort. The rewards can be dynamic to respond to incoming data, for example, reducing rewards for tasks as data goals are met.

All submitted tasks are managed using the Ona Data web application. Here, administrators can individually or bulk accept or reject submitted tasks. In our experience, most rejections are either automatic, because they violated a parameter, or are because the photo does not meet the requirements. **Figure 3** provides a screenshot of a task being validated. Here, the photo of a camel, the location and time of the task, and the domain of prices all help us check for data quality. Further, we could cross-validate this submission using data from other submissions in the same market on the same day. Rejected submissions are accompanied by justifications, whereas accepted submissions are coupled with applauding statements. The review outcomes and notes are communicated to the contributors at the mobile application interface. The reviewed data are then available for aggregation, generation of information outputs, reward calculations, and retrieval.

Mobile Platform

The KAZNET mobile application is an integration of a tasking wrapper on top of the ODK mobile client software. The wrapper performs two main functions. The first is to create a user interface, which allows contributors to browse available tasks and related protocols (e.g., locational requirements, rewards for completion), download tasks for completion offline, manage tasks, receive feedback on tasks, and track profile-level attributes. The second is to check for conformity to task parameters, for example, that the device is within the livestock market before the contributor can complete the livestock market task.

Once the contributor selects a task that she would like to complete, the task itself opens as an ODK form. This allows KAZNET to leverage the years of investment by ODK in form development for mobile devices. The forms are then completed according to the instructions. As mentioned earlier, ODK forms have a wide variety of functions, including recording geo-points, a diverse set of question types, taking photos, and playing audio or video files. Completed tasks are saved on the device for submission when the mobile device has connectivity.

Figure 4 provides a series of screenshots of screens that a contributor would see while using the mobile application. In Panel 1, the contributor is online and uses the *Explore* tab to browse available tasks, filtering by location if they choose. To learn more about a task, the contributor can select the task. Panel 2 has a screenshot from the livestock market task information screen as an example of what the contributor might see when selecting a task for more information. Here, the administrators can provide details on the reward, location, and frequency of the task, as well as any other instructions. Contributors then download tasks that they would like to save on their device for completion later. Panel 3 shows a contributor in the *My Tasks* tab, which shows that she has three tasks available for completion, either on-line or off-line. Note that a single task can be completed as many times as the parameters allow. So, for example, once downloaded, the contributor can complete the *Livestock Price and Quality* task multiple times in each market, each week.

[4]Geofence this is a function that defines a location using coordinates (latitudes and longitudes) with the help of satellites connection with location-enabled smartphones. No tasks are allowable to be submitted outside these coordinates.

[5]Temporal gate is a time function embedded in a task to define time ranges which tasks are allowable to be completed by a contributor. Tasks performed outside theses time limits are rejected.

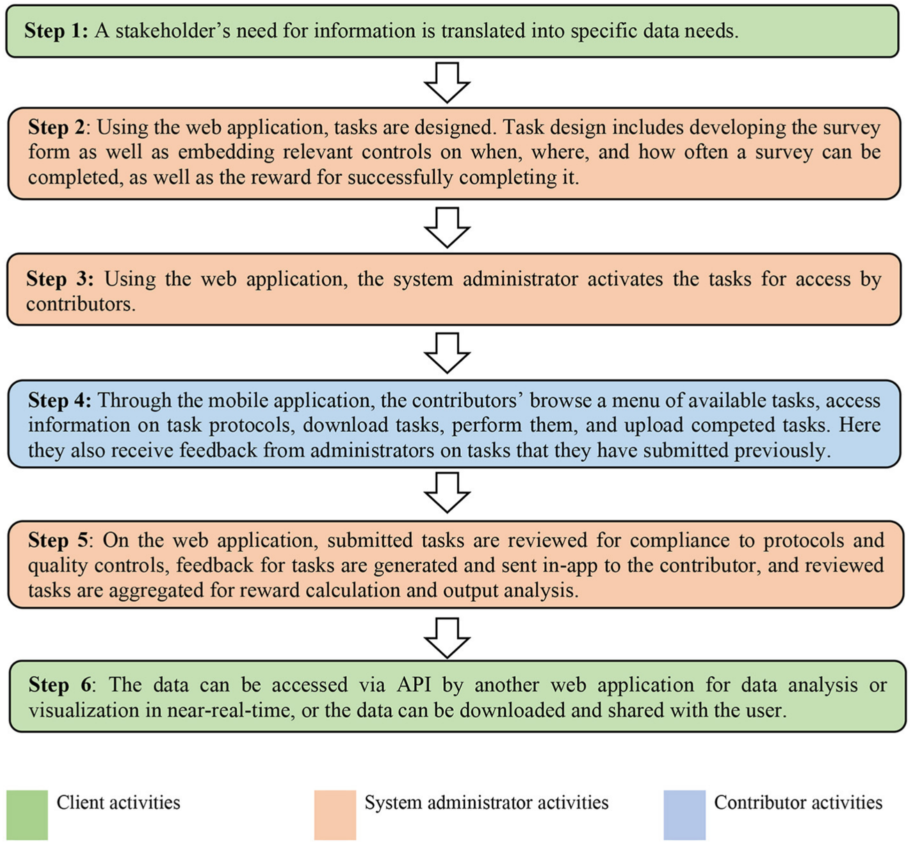

FIGURE 1 | The design flow of the KAZNET platform activities.

To complete a task, the contributor selects the task, at which time it is launched in the ODC Collect mobile client (Panel 4). Once completed, tasks are stored on the device until they are submitted, which takes place in the background when the device has connectivity. The *Submitted* tab documents the status of each completed task (Panel 5). Submitted tasks are pending, until they have been approved or rejected by an administrator, which can be done individually, task-by-task, or using spot checks and bulk acceptance/rejection, or using an automated process. When the administrator provides a comment on a task, this is indicated by a small blue comment icon on the task in the *Submitted* tab and the contributor can view that comment by selecting the task. The *Profile* tab provides a summary of the contributor's performance (Panel 6).

Both the wrapper (KAZNET) and ODK Collect are available on the Google Play Store for download. Login credentials, which includes a username and a password provided by the system administrator, are used to log in to KAZNET, which will then provide credentials to the ODK client.

RESULTS

The KAZNET platform was rolled out in 2018 to collect information on livestock markets in northern Kenya. In 2021, the network of contributors was expanded to collect data for a pilot network of 'Sentinel Zones' aimed at monitoring the impacts of climate shocks on the rangelands and the pastoralists who depended on them. Micro-tasks were developed to regularly collect data on markets, livestock production, rangelands, and human health, and, as of writing in 2022, data collection is ongoing in Kenya and Ethiopia. The next subsections use three data acquisition activities to illustrate the platform's value and flexibility.

Livestock Market Information

Livestock market data has historically been highly demanded by policy makers but has proven to be challenging and costly to collect (Stuth et al., 2006). Market information asymmetry adversely affects producers and traders, leading to losses and restricting the growth of markets (Roba et al., 2018). Indeed, there have been several large government and donor programmes in the pastoral regions aimed at collecting livestock market data, but none have provided consistent data from remote markets, which suggests demand for the data but the need for improved processes for collecting it (Kariuki et al., 2009).

In late 2018, ILRI was commissioned by the Kenyan State Department of Livestock to use KAZNET to collect livestock market information as a complement to its existing

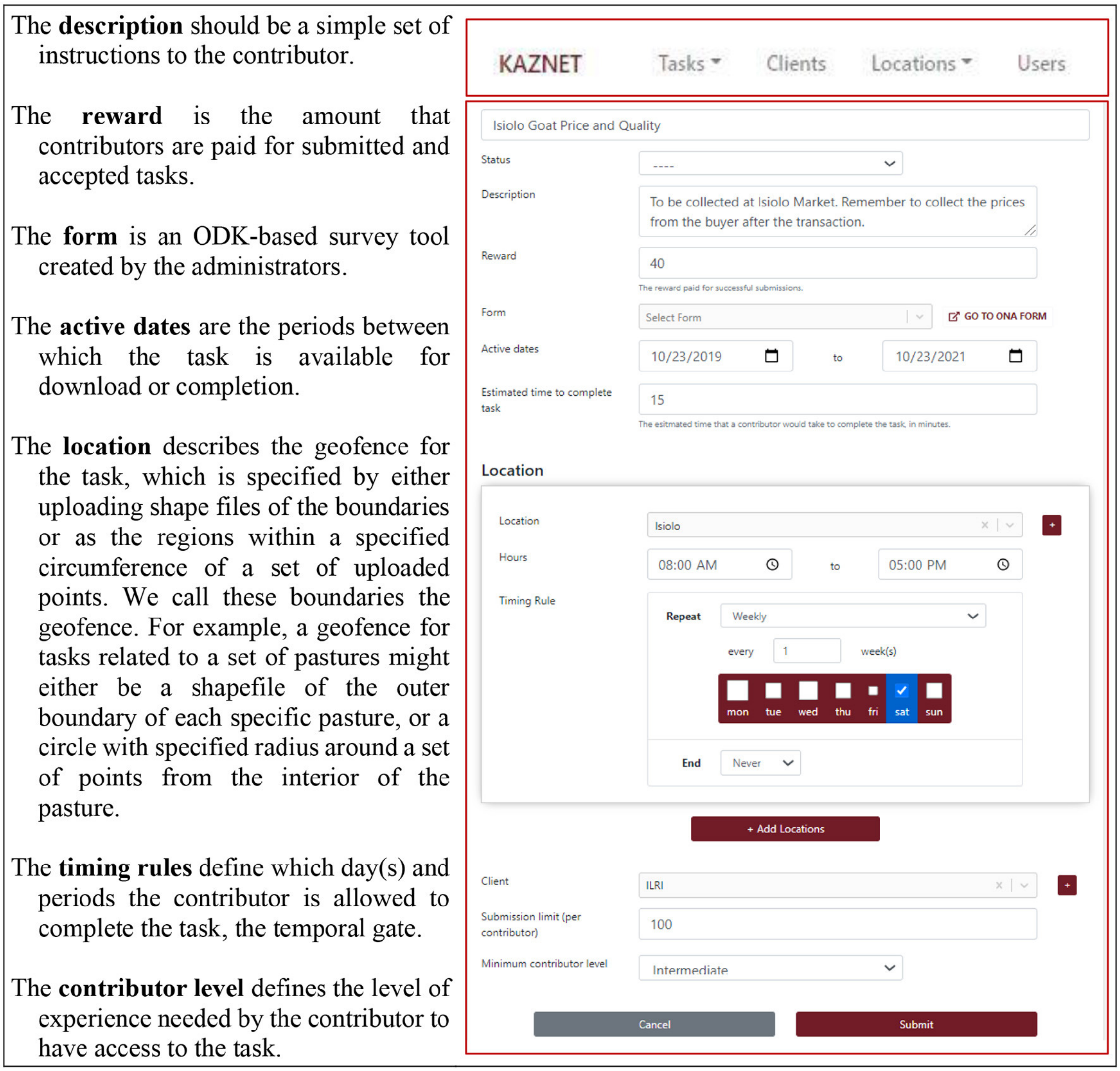

FIGURE 2 | The KAZNET web application is used to define task parameters.

national livestock market information system.[6] This was done in recognition of the fact that a micro-tasking approach might be able to overcome many of the challenges facing the existing system, which was struggling to maintain a consistent, accurate, and up-to-date database on market information from the pastoral areas.

A set of tasks was designed to address the challenges associated with conventional data collection methods while also capturing the same types of information collected by other livestock market surveys in the region. Survey forms were developed to collect information on the same indicators collected by the market monitors employed by the National Drought Management Authority in Kenya and geofencing and temporal gates were set to ensure that the data was collected only from within the livestock markets and during market hours on market days. These checks and processes are performed by the mobile application and do not require connectivity. To provide an addition opportunity for data verification, photos of the animal or livestock market in question must accompany tasks related to livestock price or market volume.

Submitted tasks first go through an automated screening process, during which some submissions are rejected automatically, at which time the contributor is notified of the rejection and reason. Those that pass the automated screening can be checked manually by an administrator, for example, checking to see if the price of a goat is accompanied by a photograph of a goat. As such, several other task-level protocols combine with web application infrastructure as well as financial incentives to define the quality and validity of the data.

[6]Information on Kenya's national livestock market system can be found at http://www.lmiske.go.ke.

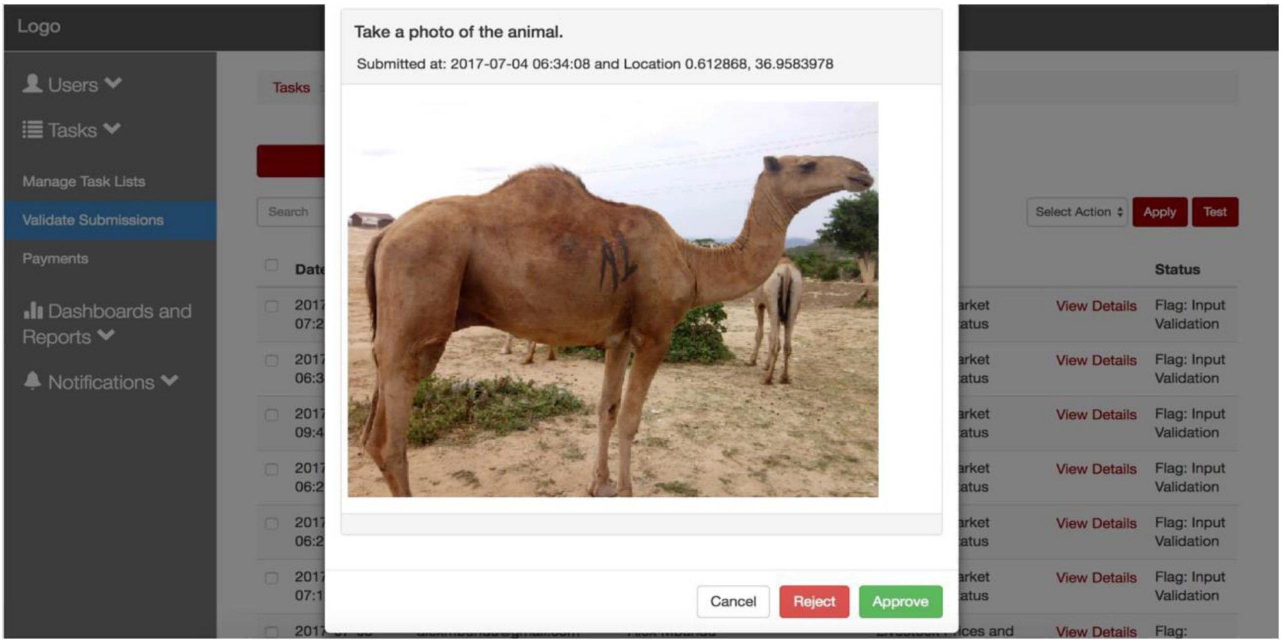

FIGURE 3 | Using KAZNET's web application to validate a submitted task by checking its photo.

It is worth mentioning that the contributors were also able to disseminate the information collected by them to their community and their own networks. For example, a task can be easily developed by asking the contributor to complete a short extension activity, such as providing information on how to respond to a current livestock disease outbreak. For more information on this use of KAZNET (see Chelanga et al., 2021).

Since 2018, data collection through KAZNET has expanded to new markets in Kenya and Ethiopia in response to demand from addition stakeholders. A network of contributors has been established in a total of 14 pastoral livestock markets (**Figure 5**). Unlike the conventional methods for collecting livestock market information, by which an individual is assigned to collect data, the network of contributors collect data throughout the day, providing a dense cloud of data that captures the great deal of variation that exists within livestock markets.

As a demonstration of the data collected, we use the example of goat prices. **Figure 6** illustrates weekly mean goat prices from across 10 livestock markets in northern Kenya, disaggregated by contributor-assessed body type. As expected, prices are related to body type; fat goats are more expensive than moderate, and the latter are more expensive than thin or emaciated goats. Alulu et al. (2020) use this data to show that more than half of the variation in the price of goats is explained by body type. Here we note that the red vertical line between March and April 2020 marks the onset of restrictions in Kenya related to the COVID-19 pandemic. During the period to the right of the vertical red line, movement was restricted in Kenya and most field operations, including most field-based data collection activities, were disrupted, highlighting another advantage of crowd-based data collection processes. Interestingly, the COVID-19 pandemic has had no discernible impact on prices.

Child MUAC and Household Milk Production

Tracking indicators of household nutrition is important for informing policies aimed at reducing malnutrition and improving the welfare of households. Effective policy formulation requires high quality and high spatial-temporal resolution data and is a great need for household-level nutrition data to better understand priorities in tackling malnutrition (Hawkes and Fanzo, 2017). In many instances, data used to compute regional and global malnutrition estimates are obtained from a single or annual survey, which limits our ability to distinguish between seasonal variation and annual averages, although those figures are rarely presented as a seasonal estimate (World Health Organization, 2019). Other nationally representative surveys are representative at low resolution, so appropriately aggregating their data can often mask variations in sub-regions, especially in hard-to-reach areas (Akombi et al., 2017). Further, pastoralists in remote regions are often underrepresented in such supposedly nationally representative surveys (Wild et al., 2019).

Micro-tasking has been applied to this data gap. Here, micro-tasking offers an opportunity to collect high-frequency data from households with little burden to the household, because the data collector is a local individual that can schedule data acquisition at the convenience of the respondent and there is little or no transportation, lodging, or food costs to support the contributor. The network of contributors can collect data on a weekly basis or even daily for target households, depending on how the tasks

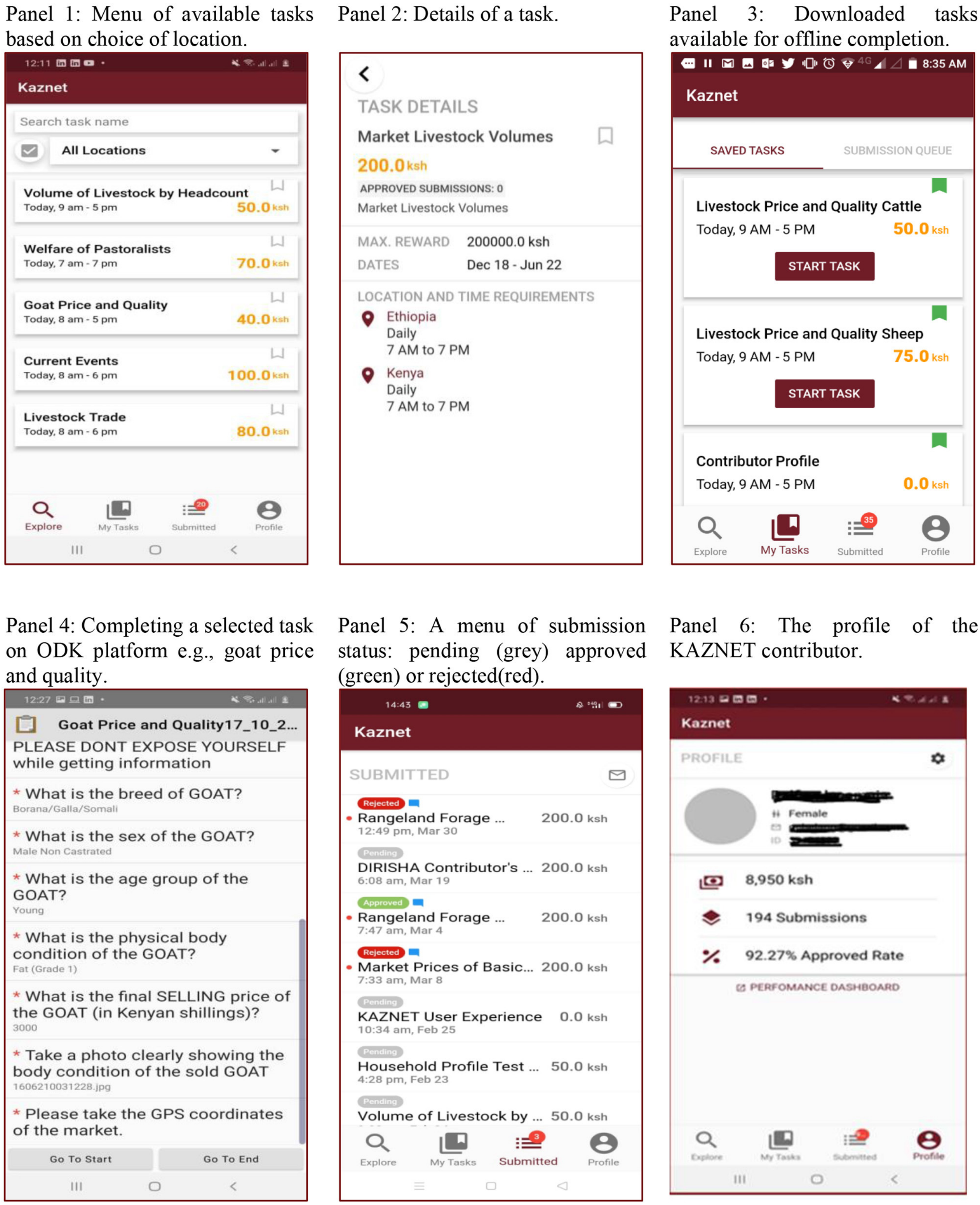

FIGURE 4 | The KAZNET platform front end schema.

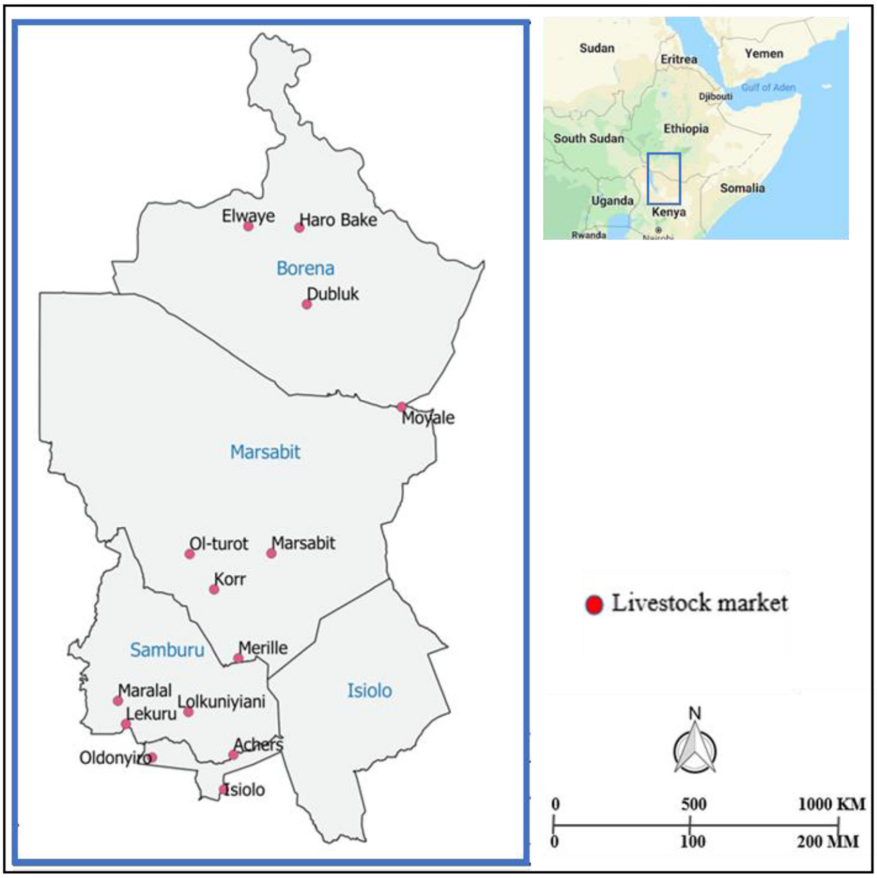

FIGURE 5 | Sampled livestock markets in pastoral drylands of Kenya and Ethiopia.

are parameterized. Such high-resolution data can capture the spatial and temporal dynamics of households' food consumption and nutrition that can be missed by infrequent surveys or cross-sectional surveys (Lepariyo et al., 2020).

To test this approach, KAZNET was used to collect a set of indicators on child consumption and nutritional status. Specifically, Mid-Upper Arm Circumference (MUAC) measurements were collected from the children between 6 and 59 months from 64 households in the drylands of Kenya and Ethiopia, as part of the 'Sentinel Zones' monitoring network. MUAC measurements are commonly used for tracking the nutritional status of children because the measurements are both sensitive to nutritional status and the materials required to make the measurement, a simple MUAC tape, are much less expensive than those used to measure weight and height (Myatt et al., 2006).

Contributors living within the communities measured, recorded, and submitted data from eligible children. A one-time training on the platform and how to measure MUAC was provided to contributors.[7] Longitudinal data was collected on weekly cycles from the eligible children in target households. The recorded numeric measurements are complemented by images of the tapes' final reading position on the child's arm. These photos are used to reject submissions, encourage better measurements, and identify issues with measurement techniques. This process of using photos to verify and learn from submissions has proven useful for our team in other circumstances.

Figure 7 presents the weekly mean MUAC data from the youngest child in the sampled pastoralist household in Kenya and Ethiopia.

The results demonstrate that KAZNET can generate plausible MAUC values and progression over time, weekly, which is extremely uncommon to see from standard field surveys. Naturally, the data can be further disaggregated, for example, by location, household wealth, and other factors that one might believe are important for learning about the progression of nutritional status.

With this level of detail, the dynamics of MUAC could be compared with those of other relevant indicators tracked over the same period to better understand the dynamics effecting nutrition. Household milk production data are among the feasible and relevant indicators that could drive child nutritional status in this region. Milk is one of the primary outputs of

[7]Certainly, all standard survey protocols were performed, including community entries, project introductions to the households, contributor introductions to households, and consent was collected.

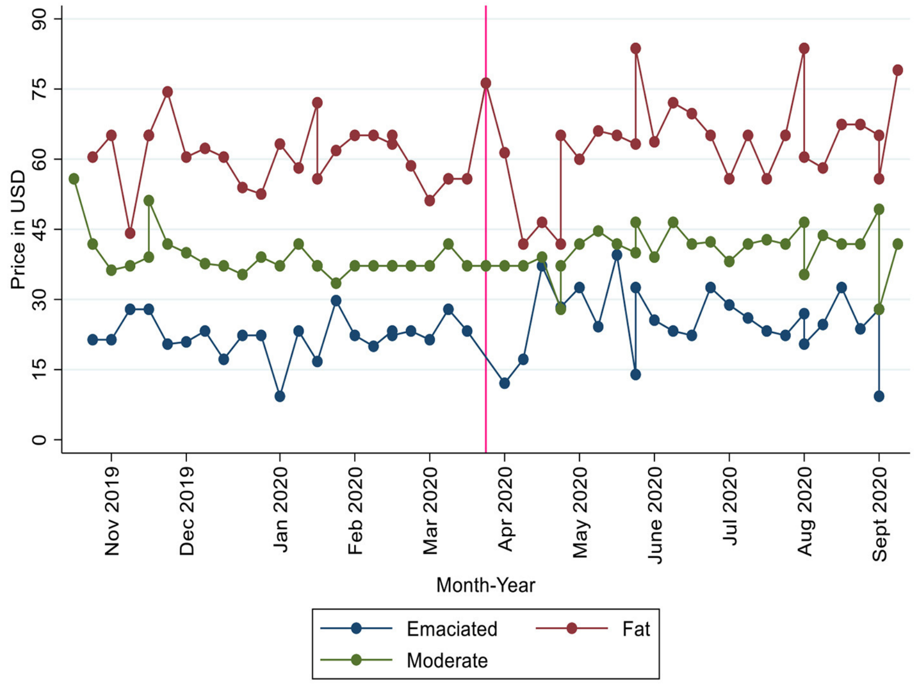

FIGURE 6 | Weekly mean goat price by body condition in 10 livestock markets in the Kenyan drylands. The red vertical line indicates when COVID-19 related restrictions started in Kenya.

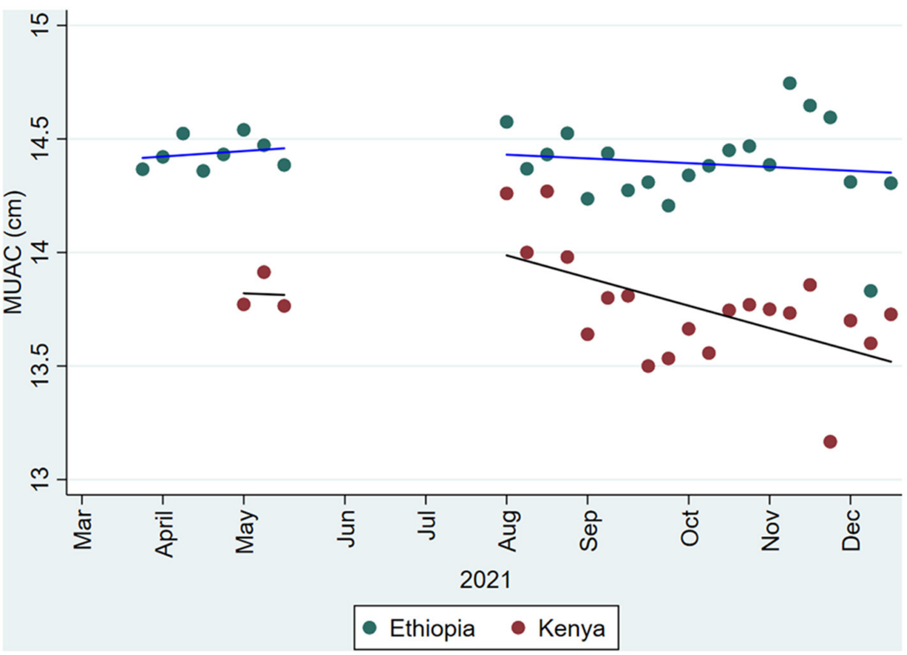

FIGURE 7 | MUAC measurement of the youngest child in the household.

the pastoral production system, is consumed frequently and in substantial quantities by many pastoral households, and has been shown to play a large role in nutritional status of children (Grace et al., 2018). At the same time, milk production and consumption in pastoral households is notoriously difficult to track accurately with conventional field surveys because it various dramatically within a household over time and because many different types of containers are used for milking. **Figure 8** includes 24-hour milk production, collected once per week, from the households of the children whose MUAC was measured and presented in **Figure 7**. For context, the long rainy season usually starts in March and continues through May. Here we see an increase in milk production, which is consistent with the build-up and availability of forage in the rangelands. We look forward to determining if the increase in milk production has any (lagged) impact on the MUAC of children in these households. Such an analysis would not be possible with cross-sectional or annual longitudinal surveys, and such high frequency data would be cost-prohibitive with conventional field survey methods.

Rangeland Data

Understanding the spatial and temporal dynamics of rangeland conditions in pastoral drylands is of critical importance because of the tight link between vegetation availability, resource-use patterns, herd management practices, pastoralist livelihoods and household welfare (Briske, 2017; Liao et al., 2020). But monitoring rangeland conditions is hampered by the extensiveness and remoteness of the pastoral region, the heterogeneity of vegetation communities, the short-term and quick vegetation response to rainfall, the complex grazing patterns linked to herd mobility practiced by the pastoral communities (Pickup et al., 1998). This makes accurate ground monitoring efforts extremely costly and time consuming, thus largely unfeasible on a regular basis. As a result, the availability of data on rangelands is extremely scarce and, when available, ground datasets are of limited quality or spatial/temporal resolution (Zezza et al., 2016).

To overcome this challenge, Earth Observation (EO) is seen as the only viable solution to regularly monitor indicators of rangelands condition in pastoral regions. Long term datasets of vegetation indices measured from satellite optical sensors onboard satellites are currently operationally used for continental and regional monitoring of rangelands (Fava and Vrieling, 2021), but they lack the spatial resolution for informing local-scale application and pastoralist tactical decisions on grazing management. Novel EO sensors and data, such as the one collected by the Copernicus Sentinel fleet or Planet Scope, provide the opportunity to improve rangeland monitoring at high frequency and high resolution (Zhang et al., 2019; Cheng et al., 2020). The Sentinel 2 mission, for example, acquires data globally every 2–5 days at up to 10 meters resolution. However, management-oriented applications require quantitative estimation of rangeland condition indicators such as herbaceous biomass, bare ground/vegetation cover or vegetation composition, and this can be achieved only by calibrating and testing EO-based models using ground datasets. Thus, ground data collection remains of paramount importance to improving our understanding of rangelands and developing models to support pastoral communities.

Cost-effective data collection processes for the rangelands have been developed, such as the Land-Potential Knowledge System (Herrick et al., 2013) or the VegMeasure tool (Louhaichi et al., 2018). These digital applications allow collecting data *via* mobile phones with relatively simple protocols and have been

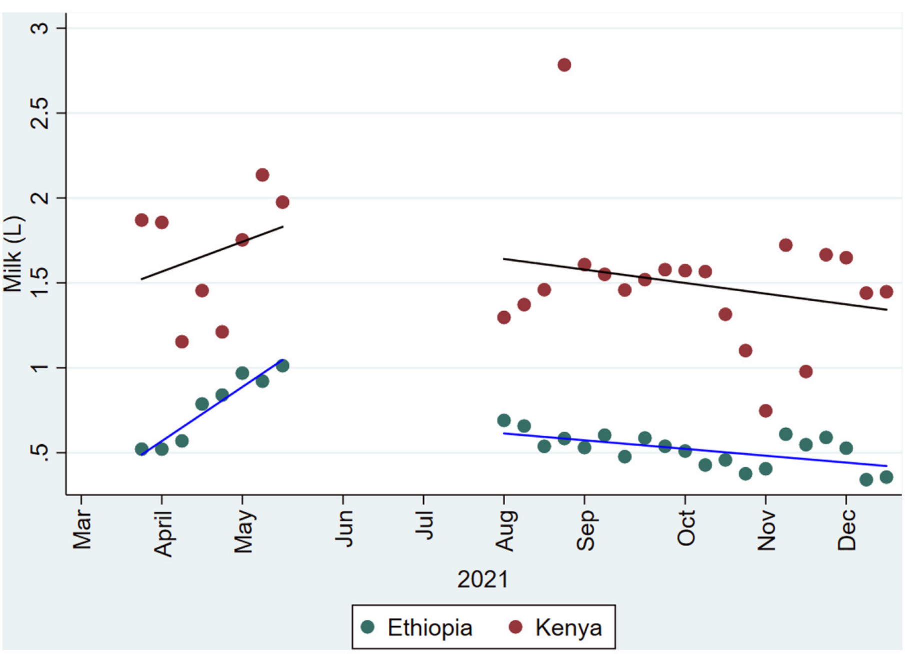

FIGURE 8 | Twenty-four-hour milk production of sampled pastoral households in Kenya and Ethiopia.

proven valuable by several applied research studies. However, they are not designed with a micro-tasking approach for agile data collection, and this limits their flexibility of use for multiple data collection objectives, including high-frequency rangeland monitoring.

Here we illustrate an example of how the KAZNET platform has been used for monitoring 32 pasture sites across two regions of Kenya and Ethiopia, as part of the "Sentinel Zones" monitoring network. The network and data collection protocols have been designed not only to gain an understanding of rangeland dynamics in the specific locations, but also to evaluate the relationship between ground observations and Sentinel 2 satellite data for remote sensing model calibration and testing. To this end, representative pasture locations were selected by local communities and the starting and ending point of 100 m linear transects for vegetation monitoring were marked. A KAZNET task was then developed to collect: (i) geo-tagged nadiral down-looking pictures every 10 m along the transect for the assessment of vegetation and bare soil covers, (ii) landscape pictures in the four-cardinal direction for site characterization, and (iii) supporting information about animals grazing in the area. Data are collected with a frequency of 7–10 days. The nadiral pictures, after quality check and validation of the task, are processed automatically through unsupervised image classification techniques using the Canopeo open tool (Patrignani and Ochsner, 2015) to estimate the green vegetation cover (**Figure 9**).

Figure 10 provides two examples of vegetation cover time series collected over dry (S1) and wet (S2) season pastures in Ethiopia between March and June 2021, which corresponds to

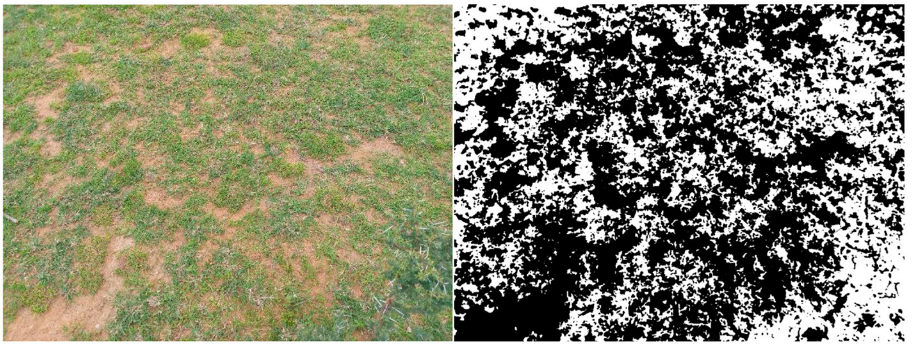

FIGURE 9 | Digital image collected *via* mobile phone using the KAZNET platform. On the right, the classified image used to calculate the green grass cover.

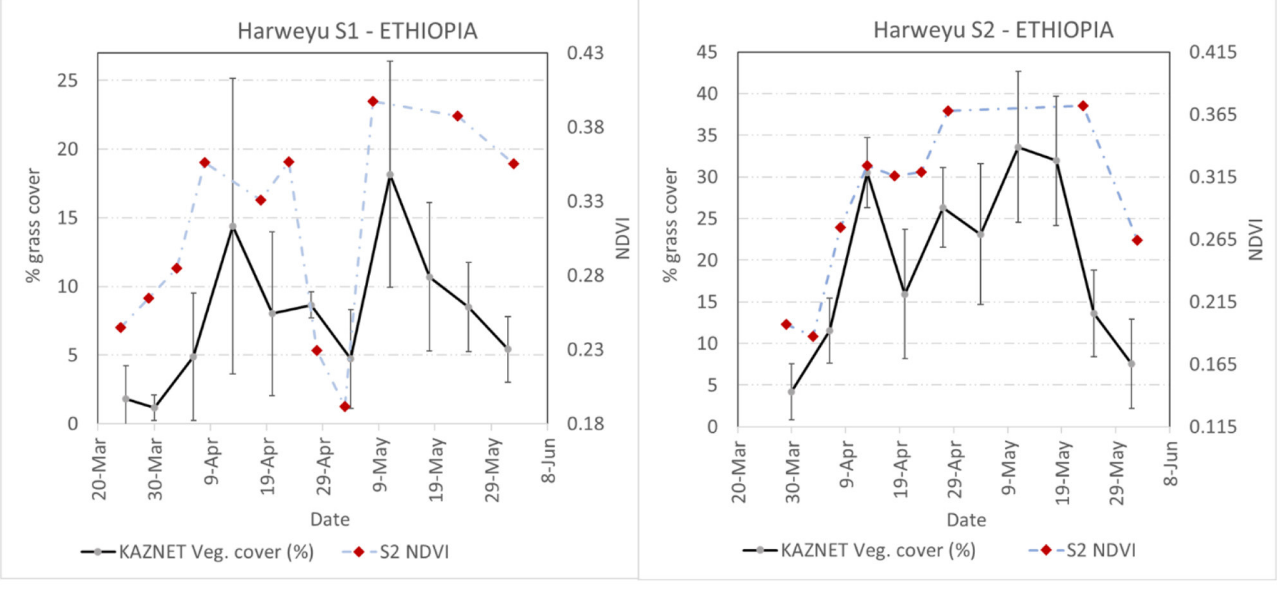

FIGURE 10 | Percent green grass cover estimated from KAZNET for a dry season (S1) and a wet season (S2) pasture in Ethiopia between March and June 2021. Red dots indicate the Sentinel 2 NDVI values acquired over the same sites.

the first vegetation growing season (Belg) in the region. The data well captures the growing season's late start at the beginning of April and the end of the season toward the end of May.

The figure also includes time series of Normalized Vegetation Differenced Index (NDVI), an indicator of green biomass, for the same pastures. The coherence between the percent of grass cover from KAZNET and NDVI is very good for both sites, supporting the overall quality of micro-tasked ground observations. Interestingly, rapid dynamics of green grass availability, likely associated with rainfall or grazing events, are captured very well by KAZNET data, and can be confirmed by ancillary information collected by contributors on livestock presence and recent rainfall events. These sporadic events, for example during late April at the Harweyu S1 transect, are instead very difficult to capture and correctly interpreted by satellite data analysis because of potential uncertainties caused by cloud cover and other potential noise in satellite data time series that cannot be resolved without ground truth information.

Overall, the KAZNET micro-tasking approach coupled with a simple data collection protocol based on geotagged pictures has the potential to address critical information gaps in pastoral drylands related to rangeland vegetation dynamics. The protocol requires minimal training and can be easily executed by a large number of contributors that can conduct repeated observations over the same area with high frequency. Contributors can visit pasture sites close to their village or satellite camp during seasonal transhumance, thus minimizing the costs of reaching locations that are often remote and not easily accessible without local knowledge. Finally, while the illustrated example focuses on using the platform for monitoring purposes, the flexibility of the micro-tasking approach allows introducing additional questions or data collection points when necessary, for example, to better understand the cause of a rapid change in vegetation cover (e.g., locust invasion, fire), to evaluate the impact of a restoration intervention, or to better evaluate the effect of climate shocks (i.e., drought and floods) on forage resources over specific locations.

Cost Assessment

Reducing costs and thereby increasing the frequency of data that can be collected is one of the main objectives of KAZNET and micro-tasking more generally. To assess costs, it is helpful to first identify those activities that are more or less identical for KAZNET and conventional methods of data collection. Both approaches require survey tool development, developing a sampling protocol, recruiting, and training individuals to collect the data, paying data collectors and respondents for their time, setting up processes for data screening and cleaning, and general project management. The main difference is that for KAZNET, the data collectors are engaged continuously so that there are no additional recruitment and training rounds needed for additional rounds of data collection, and the data collectors live in the areas that they collect data from so that there are few of the costs related to transporting, feeding, and lodging teams of enumerators away from their home. To put these costs in perspective, total direct field expenditure by ILRI to collect a household survey in 2020 from 1,800 participants in northern Kenya was about USD185,000.[8] Of that, USD35,000 was directly related to enumerator training, USD62,000 was for feeding and lodging the field teams during data collection, and USD 21,000 was spent on transportation for the enumerator teams during data collect. Together, these costs account for about 64% of the total budget of that activity. In 2022, ILRI is about to collect an additional round of data from that same households. The level and profile of the expenses for this additional round are nearly identical to that of the 2020 round.[9]

The micro-tasking approach does require the initial training for the data collectors, but then uses that training to its full potential by engaging the trained data collectors for many rounds of data collection. There are additional costs to collecting many rounds of high-frequency data through KAZNET though, specifically the payments to the data collectors for completing tasks and any payments to respondents. Back of the envelope calculations show that for the sentinel zone sample, the budget required to set up and collect the existing tasks weekly from the 64 households, 8 markets, and 32 pasture transects for a year, would be sufficient to collect two annual panels (e.g., baseline and endline) of a more conventional survey from the same 64 households, 8 markets, and 32 pasture transects. We note that conventional data collection approaches usually try to offset the extremely high fixed cost of reaching each survey respondent by asking many questions. In KAZNET, those fixed costs have been reduced dramatically, which also means that there is more focus on the marginal cost of additional questions, leading to the use of much shorter and more focused survey instruments. The result is that conventual methods usually collect information on many more aspects of individuals and households than does the KAZNET approach. This cost-neutral comparison highlights that the objectives of data collection that should determine its approach. Are those objectives better met by conventional detailed surveys of households at low frequency or higher frequency and focused data?

DISCUSSION

Micro-tasking is one feasible option for overcoming many of the challenges and costs of data collection that conventional methods face, especially in regions difficult to reach or when targeting individuals that are mobile. The data collected through the KAZNET platform supports the notion that micro-tasking can be used to collect accurate, high frequency data on various dynamic indicators that have proven difficult to collect using conventional field survey methods. The breadth of tasks and related data

[8]The authors recognize that these amounts may seem high to many readers familiar with collecting data in rural but less remote or less arid regions. There are a number of special features to pastoral regions that drive costs up substantially including: a low population density, mobile households, extremely poor roads requiring rental of expensive 4 x 4 vehicles, lack of connectivity so that mobilization is challenging, interruptions to data collection from conflict, and households that can only be reached by walking several hours.

[9]Due to COVID and related restrictions on gatherings, the cost of training will actually increase by about 30%.

collected through KAZNET demonstrates the flexibility of the platform to meet diverse needs. In all cases employed, the cost per datapoint were much smaller using KAZNET than if the data had been collected using conventional methods. While it is important to monitor the quality of data generated by micro-taskers and have mechanisms for ensuring quality, the issue is no different than that faced by conventional methods, except that, with micro-tasking, the data-user is likely to have a richer dataset that can be used for intertemporal and cross-sectional validation and cleaning.

Furthermore, there are many benefits to being able to update and adjust what, when, and where data are being collected, in near real time. The flexibility of rapidly expanding the network, through remote and/or peer-to-peer training and remote onboarding, allows managers to respond to the dynamic data needs of their clients. This flexibility also minimizes data gaps across space and time. For instance, gaps in market price data are less likely to occur if markets have several contributors collecting data from them simultaneously, and the absence of any particular contributor does not interrupt the flow of data. Flexibility in data type and the ability to change tasks is a huge benefit in some situations. For example, at the onset of the COVID-19 pandemic in 2020, it was quick and easy to create a set of shock-specific tasks that were rolled out and completed despite the restrictions imposed on movement between the location where researchers and managers were, and where the data were (see Chelanga et al., 2020; Graham, 2021).

The micro-tasking approach is also very conducive to learning objectives. Randomization of access to tasks or treatments through the platform is possible, as is adjusting and experimenting with rewards structures, contributor quality ranking, and access to additional resources, such as information. For example, Chelanga et al. (2021) tested if access to market price information, which was generated by processing data from the contributors, was an incentive for those very same contributors to provide more or higher quality data.

None of this is to suggest that the micro-tasking approach is always, or even often, a preferred substitute for other methods. In cases where other approaches are working well, there may be no reason to consider other options. Indeed, large socio-economic field surveys (e.g., Living Standards and Metrics Survey—LSMS -of the World Bank Group) are the workhorse of several academic fields, and those surveys fit the needs of many researchers in those fields well. Such long and in-depth assignments require a great deal of training and logistical precision that would almost certainly be difficult to replicate through a micro-tasking platform. However, the high costs of these long household surveys and other field methods have also clearly led to suboptimal availability of data in many cases, much of which is in difficult-to-reach places or among difficult to reach people, which is not coincidental. The above findings suggest that there can be advantages to using micro-tasking and that a diverse set of data can be collected well in this way. Broadly, it seems that micro-tasking should be considered in situations where near-real-time, high-frequency, difficult-to-collect information is needed or if flexibility in scale and scope is important.

In addition to micro-tasking not being appropriate for all types of data collection exercises, there are also some other factors that implementors should be aware of. First, while the implementation of data collection is relatively simple, the process of setting-up and managing a micro-tasking network of agents is a considerable undertaking. Furthermore, there are fees related to server space and payments directly to the contributors, which add up to the operational expenses. Many of the expenses, such as server rental and staff-time for network management and platform maintenance, are mostly fixed, so that they can be spread over several projects, but contributor payments, which in our experience are best made on a per-task basis, scale directly with the amount of data collected, and this can be a risk to sustaining long-term, high-frequency, data collection objectives. That is, while micro-tasking can have a very low cost per data point, the fundamental trade-offs between sampling density/frequency and costs remain so that researchers should continue to use careful sampling strategies consistent with their specific data collection goals and budgetary constraints.

Moving forward, work continues to create additional functionality and streamline processes. Lessons learned during management of the platform, evolving data needs, and clients feedback provides valuable inputs for further improvement of the KAZNET platform and learning related to micro-tasking. For instance, the recent round of feedback and development led to the new in-app feature by which contributors receive submission-level feedback on the quality of their submission and its status (pending, accepted, rejected)—which improves transparency of the accept/reject process and, in turn, payments, acting as an immediate source of feedback and training. Contributors and managers have found this additional feature extremely useful, and it has translated into improved data quality and improved contributor satisfaction.

While KAZNET has proven to be a valuable tool for a number of projects in pastoral regions of Kenya and Ethiopia and public institutions have expressed interest in adopting the platform for data collection and monitoring purposes, it is currently managed by a research organization with no mandate for service provision and limited expertise in managing such networks or software development. For micro-tasking to realize its full potential, it is likely that the private sector will need to take it up, perhaps with public support, and offer data collection services for a fee. Such firms may be able to manage teams of contributors more efficiently than ILRI has been able to and would hopefully be able to draw a wider client-base, including public institutions, which could help increase the breadth, diversity, and skills of contributors by aggregating demand. Such services could be extremely helpful in increasing data availability from data scarce regions.

DATA AVAILABILITY STATEMENT

The data analyzed in this study is subject to the following licenses/restrictions: the data are under a 12 month embargo. The data will then be placed in the public domain. Requests to access these datasets should be directed to n.jensen@cgiar.org.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Institutional Research Ethics Committee (IREC), ILRI. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

PC and NJ lead the development of this manuscript. VA, PC, FF, and NJ provided original material for this manuscript. VA, RB, MB, PC, FF, DG, WG, NJ, WL, ON, KM, and MT contributed equally to the conceptualization and development of the KAZNET platform. All authors contributed to manuscript revision, read, and approved the submitted version.

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METHODS
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A Flexible, Extensible, Machine-Readable, Human-Intelligible, and Ontology-Agnostic Metadata Schema (OIMS)

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This paper presents a lightweight, flexible, extensible, machine readable and human-intelligible metadata schema that does not depend on a specific ontology. The metadata schema for metadata of data files is based on the concept of data lakes where data is stored as they are. The purpose of the schema is to enhance data interoperability. The lack of interoperability of messy socio-economic datasets that contain a mixture of structured, semi-structured, and unstructured data means that many datasets are underutilized. Adding a minimum set of rich metadata and describing new and existing data dictionaries in a standardized way goes a long way to make these high-variety datasets interoperable and reusable and hence allows timely and actionable information to be gleaned from those datasets. The presented metadata schema OIMS can help to standardize the description of metadata. The paper introduces overall concepts of metadata, discusses design principles of metadata schemes, and presents the structure and an applied example of OIMS.

Keywords: metadata, interoperability, data management, reusability, JSON (Java Script Object Notation)

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INTRODUCTION

Prior to the COVID-19 pandemic, it has been estimated that international agricultural research for development (specifically CGIAR) alone collected household survey data from a quarter-million farmers each year. Along with the data collected by other entities and published in open access, such as the World Bank LSMA ISA datasets (https://www.worldbank.org/en/programs/lsms/initiatives/lsms-ISA), the FAO household data (https://data.apps.fao.org/catalog/dataset/household-survey-data-portrait), these datasets can potentially provide valuable insights into smallholder farming and key aspects of agri-food system transformation. However, interoperability of these datasets is a major challenge. In socio-economic data, there is a notable lack of widely accepted standards. Standardization of both questions and the way they are asked is challenging. Questions are often context specific related to the location and cultural context in which the data is collected and the specific research questions underlying the data collection.

There is an increasing requirement for publicly funded research organizations to make the data they collect available as global public goods. While this is the main driver behind many open access/open data initiatives, there are other more compelling reasons to work toward well-organized data repositories. The cost of collecting data (again) often outweighs the costs of organizing it. Once it is well-organized the data can be repurposed for other research purposes. Very often, only a part of the data collected is actually used in the research for which it was initially intended. Making the data accessible can create value beyond its original purpose for more researchers than those who originally collected and/or analyzed the data. To be able to use and re-use data effectively and efficiently, and to provide data to the world as a global public good it is imperative to implement user friendly data management systems.

Agile, data-oriented research tools can help to overcome these challenges. The term "agile" in this context is used to imply methods that are designed to be easy to use, which entail some degree of flexibility in terms of adaptation to local conditions and integration with other tools or methods. This helps to address the major challenges facing smallholders in the context of agri-food system transformation. Smallholders face complex dynamic circumstances, and the data for analysis of those circumstances are also dynamic and complex. Standardization is often lacking, and approaches are needed to ensure interoperability of the various datasets needed for actionable research.

It is very important to distinguish between data and metadata. In the original FAIR data guidelines (Wilkinson et al., 2016) data and metadata were grouped. FAIR stands for Findable, Accessible, Interoperable and Reusable. Not distinguishing between data and metadata has a certain appeal because metadata itself is a form of data. While that makes sense for the human intelligible aspects of making data FAIR it has a different connotation for the machine-readable aspects of the standards. Because we focus on the standardization of metadata instead of the data it describes, we must be meticulous about our metadata definitions.

We, therefore, need to make a distinction between different types of metadata (Cundiff, 2004; Cantara, 2005). There are three main types of metadata with some subtypes: descriptive metadata, structural metadata and administrative or technical metadata. These concepts are very often used interchangeably leading to poorly defined metadata and hindering open and FAIR data. This will be discussed in some more detail in the next section on design principles. In this context, the notion of structural metadata referring to the actual content of datasets is vitally important. Being able to readily use datasets to address issues related to agri-food system transformation requires a metadata schema that is flexible and extensible.

Both in the private sector as well as in not-for-profit organizations, the issue of data management in relation to the ever-increasing amount of data is a hot topic. In the domain of agricultural research this is no different, data from different scientific domains are present and increasingly there is a need to combine data from different domains to glean new insights. There is a heated and ongoing debate on the concept of data lakes and its usefulness for managing the ever-increasing volume, variety, and velocity of data. All organizations must adopt data management strategies that keep up with the advent of big data if we hope to conduct research effectively and accurately. In the private sector, data management is often referred to as master data management (MDM) (Rittman, 2008) which comprises the processes, governance, policies, standards, and tools that consistently define and manage an organization's critical data to provide a single point of reference. Metadata is an essential component of data management. In the context of international agricultural research for development, data management complexity is even greater as data is coming from many different sources.

Twentieth century data management strategies focused on ensuring data was made available in standard formats and structures in databases and/or data warehouses (Inmon, 1992; Russom, 2013)—a combination of many different databases across an entire enterprise (Oracle, 2002). The major drawback of the data warehouse concept is that it works like a straitjacket acting as a disincentive to corporate level data repositories.

One alternative storage and retrieval system that can handle high variety data is the data lake. It is one of the newest flavors in MDM (O'Brien, 2012; Cap Gemini Pivotal, 2013; Knowledgent, 2014; PWC, 2015). While it is still a controversial concept it is the most promising for research purposes. Data lakes are a store-everything approach to big data, and is a massive, easily accessible, centralized repository of large volumes of structured and unstructured data. The Data Lake is a data-centered architecture featuring a repository or set of repositories capable of storing vast quantities of data in various formats. Data from many different sources such as webserver logs, data bases, sensors, satellites, surveys, social media, and third-party data is ingested into the Data Lake.

However, without metadata—information that describes the data we are collecting—and a mechanism to maintain it, data lakes can become data swamps where data is murky, unnavigable, has unknown origins, and is ultimately unreliable. Every subsequent use of data means, scientists and researchers start from scratch. Metadata also allows extraction, transformation, and loading (ETL) processes to be developed and take place, which retrieve data from operational systems and process it for further analysis (Lane, 2005). The data collected in international agricultural research often resembles a data swamp instead of a data lake. Data sets often lack adequate metadata. If metadata is present, it tends to be limited to descriptive metadata. In the case some detailed structural metadata is provided, this is often in the form of an idiosyncratic data dictionary.

In international agricultural research for development focusing on the transformation of complex dynamic agri-food systems, data from many different domains are used from genomic data, remote sensing and satellite data, and crop management data to socio-economic data. Some of these data have some level of standardization like genomic data, while for instance socio-economic data consisting of high variety structured, semi-structured and unstructured data suffers from an almost complete lack of standardization.

In this paper, the first version of a light-weight metadata schema is presented that is flexible and extensible so that it can be used for the wide variety of household-level datasets used for the analysis of smallholders and agri-food system transformation. In the next section, the design principles are discussed, followed by the structure of the metadata schema. The approach and metadata schema are then used to tag a portion of a farm household dataset as an example.

DESIGN PRINCIPLES

Metadata Typology

As mentioned earlier, metadata can be subdivided into categories (Cundiff, 2004). The first type of metadata is administrative metadata. Administrative metadata relates to the technical source of a digital asset. It can be subdivided into three subtypes: technical metadata which we define as *information necessary for decoding and rendering files*; Preservation metadata which is defined as *information necessary for the long-term management and archiving of digital assets*; and rights metadata defined as *information pertaining to intellectual property and usage rights*.

Descriptive metadata is essential for discoverability and identification of digital assets. This is the most common type of metadata used for finding relevant data assets in open data repositories. It describes the data asset in terms of concepts such as "author," "title," "publisher," "abstract" and "keywords," to name a few. This is the most common type of metadata attached to research data information products. Examples include Dublin Core metadata schema (https://dublincore.org/) and the CG Core metadata schema (Devare, 2017).

Structural metadata is data that indicates how a digital asset is organized and that act as identifiers and descriptors of the data. Structural metadata facilitates content reuse by providing detailed information about the structure of the content of the digital asset. It can therefore be defined as *data defining the logical components of complex or compound objects and how to access those components.* Structural metadata comprises most of what is traditionally considered metadata that is organized as the data dictionary, and can include: data element information, table information or record structure information, depending on the data asset.

The lack of structural metadata in an easily accessible way that allows searching high variety datasets is arguably the greatest challenge to turning existing data into new actionable information (Rasmussen, 2018). Metadata schemas tend to be focused on specific domains (Canham and Ohmann, 2016), stop at a very high conceptual level (Shukair et al., 2013) or focus on descriptive metadata with a fixed structure (Devare, 2017; Labropoulou et al., 2020). Specific metadata schemas exist for specific datasets. For socio-economic datasets the Document, Discover and Interoperate (DDI) approach (https://ddialliance.org/) exists (Rasmussen, 2014).

The DDI/XML approach to managing metadata is elegant and comprehensive, but due to its complexity, very difficult for individuals to manage on their own, because it usually requires large scale projects to implement with varying success (Vardigan et al., 2015). DDI as a metadata schema for socio-economic data was first developed in the mid-1990s (Vardigan, 2014). A key example of successful implementation in the domain of smallholder agriculture is the World Bank LSMS ISA datasets that use the metadata approach. In agricultural research for development, there are seldom sufficient resources to implement a heavy weight approach like DDI. Moreover, investment in a heavy-weight approach makes more sense when the same types of data are collected on a regular basis in multiple settings by the same organizations managing the data assets. The key lesson that can be drawn from the DDI experience is that there is a need for a light-weight approach that is compatible with other approaches.

Data Entity Approach

A Data Entity, is a top level container of information (Esteva et al., 2019). From a machine perspective it is most relevant as a data object that has a unique uniform resource identifier (URI) (Berners-Lee et al., 2005) and at least some technical metadata. From the human perspective, the relevancy of a data entity is that of a data concept, something that has meaning for humans and hence has some descriptive metadata. Data objects and data concepts can coincide but do not have to do so necessarily. An example of a data entity as a concept and not an object is a data collection. A data collection is defined here as a number of datasets that are somehow related. The datasets are data objects with a distinct URI. The data collection encompasses data objects but is not a data object itself.

Data entities can have parent child relationships. An example is a dataset. A farm household-survey dataset in an open-access repository is an example of a data entity, it typically has metadata describing the study, study area, authors, and contributors. It is a parent with children. The children are for instance the various data files in the dataset. Household surveys often have numerous data files covering the various interlinked tables. It is these data files that require a flexible metadata schema to describe their contents.

Data entities can also be the various supporting documentation files as well as all the relevant metadata files.

Rich Metadata Beyond Ontologies

Structural metadata describes the contents of a data file. An example of a structural metadata file is a data dictionary. Statistical software packages such as STATA (https://www.stata.com/) commonly used for farm-household data analysis actually contain some of the basic structural metadata:

- Name: variable names
- Label: short description of the variable
- Type: data type
- Format: specific format of the variable

Other metadata is not included in the STATA metadata but is essential to understand the structure and content of files. Examples of key metadata that cannot be gleaned from the STATA data files include information on primary and foreign keys and information on controlled vocabularies when code books have been used. Some metadata fields may be relevant in some cases but not others such as the way information was captured, if a variable contains restricted information, such as personally identifiable information or information on data quality.

What is deemed useful metadata depends on context, international best practices, and organizational data policies. Therefore, the metadata schema must be flexible and extensible. The flexibility also pertains to the fact that some of the metadata may actually be included in the data file in another field. While this is perfectly understandable for a human, it can be tricky to program machines that parse datasets. It is therefore important to include this kind of information in a standardized way in the metadata file.

In recent years, within the realm of data management for agricultural research for development, a strong focus has been placed on ontologies (Arnaud et al., 2020). Ontologies are important components of formal descriptions of knowledge. They are useful where there is strong agreement about terms and their relationships. Ontologies are important, arguably necessary but are in themselves not sufficient for data interoperability. Ontologies can provide structured content in terms of values used in the metadata.

Formalized definitions of concepts are essential for interoperability across high variety datasets. Ontologies can play an important role in that formalization. Many different pre-existing domain-agnostic standards in terms of ontologies exist as well as domain-specific ones. Creating interoperability requires ontology term mappings when different ontologies are used to tag concepts. Within a metadata schema that does not depend on a single ontology, it therefore becomes essential to identify which ontologies are used to tag concepts.

Summary of Design Principles

In summary the following design principles emerge for a metadata schema that can be used easily for the high variety datasets that characterize the domain of small holder farming and agri-food system transformation analysis.

High variety implies that the schema must be **flexible** to accommodate all kinds of data. The schema must be **extensible** to address new issues, including demands for different types of metadata that currently are not prioritized. Metadata approaches such as DDI provide that flexibility and extensibility but are cumbersome to use and the metadata is not very user-friendly or human-intelligible (Amin et al., 2012). A **lightweight** approach that is **human-intelligible** is therefore the way forward. Obviously, the approach should be **machine-readable**, requiring a formalized structure in a generally accepted format. We are not operating in a vacuum, so the metadata approach should take advantage of any work already done. Ideally allowing for the automatic incorporation of existing and new data dictionary approaches. While formalized knowledge in terms of ontologies is an essential component of interoperability the approach should not be dependent on a single ontology. Being **ontology-agnostic** and able to incorporate existing metadata approaches is part of the flexibility and extensibility already highlighted as design criteria. For **reproducibility**, a versioning system must be included. For **transparency**, the information about the schema must be available in open access with relevant documentation. Furthermore, transparency requires a method that allows comments to be included meant for humans and not machines.

The DDI/XML approach was designed to allow interoperability with other metadata schemas. The same principle was used for OIMS. This implies that in principle, metadata should be exchangeable between the two approaches. Obviously, this comes at some cost as it requires a metadata schema to be described in terms of the other schema.

STRUCTURE OF OIMS

The fundamental discussion between flexibility and standardization is at the core of the way OIMS is structured. The questions we asked are provided here.

1. Would be possible to describe datasets that already have data dictionaries or other metadata without having to redo all the work data managers have already put into the process?
2. If we wanted to add another metadata element to a data dictionary, how can that be done without overturning everything?

The metadata as description of the data itself is less domain specific and less context specific as the data itself. So, if we can standardize the way we describe the metadata in such a way that it can describe any metadata field, we have the standardization we want and the flexibility. If we want to add a metadata field to a data dictionary, the OIMS schema allows us to describe the field in a standardized way.

In the following subsections we provide some of the technical details that allow this flexibility and standardization.

Metadata Schema Format

For the metadata to be machine readable, it needs to be in a format that is standard and flexible. **JSON** (Java Script Object Notation) is a lightweight data-interchange format. It is easy for humans to read and write. It is easy for machines to parse and generate (http://www.json.org/). The JSON format allows both single objects as well as arrays. See **Figure 1** for a graphical representation of JSON.

The DDI metadata approach uses XML (eXtensible Markup Language). JSON and XML are comparable in flexibility and use. The main reason for choosing JSON is that parsing JSON is much faster than parsing XML.

A Metadata Schema to Describe the Data Dictionary

As mentioned earlier metadata is data itself and hence should have metadata attached to it. In order to describe a metadata schema, we need a format for doing so.

Each metadata field can be described with the following elements

- **AttributeName**: the identifier of the metadata field is a required element both for machine-readability (MR) as well as it being human-intelligible (HI)
- **AttributeDescription**: A short description of what the metadata field entails is a required element for HI
- **DataType**: the data type of the contents of the metadata field. This allows consistency checking in automated quality assurance tools and is handy for data management purposes
- **Status**: determine if a field is: required; recommended; required if applicable; recommended if applicable; optional
- **TypeClass**: identification if a metadata field consists of multiple attributes or if the attribute has only a single value. TypeClass has two possible values: primitive and compound

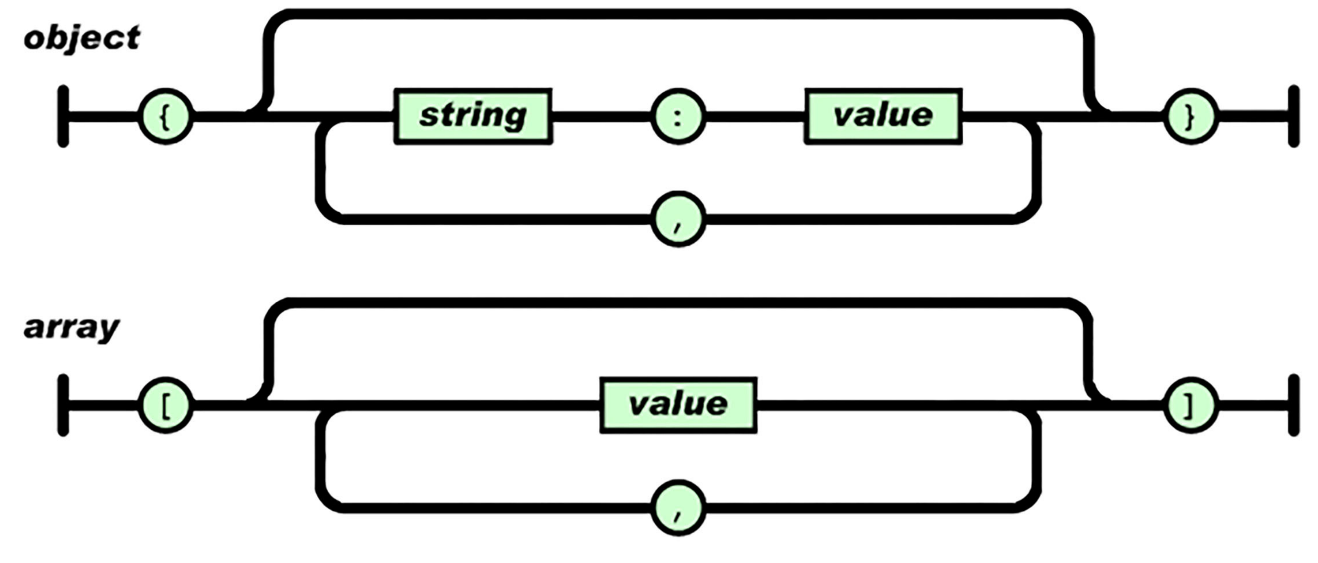

FIGURE 1 | Structure of JSON.

- **Multiple**: does a metadata field allow multiple entries or not. Multiple has two possible values: TRUE or FALSE
- **OntologyTerm**: attribute value identifier is a compound field consisting of several sub-elements.
    - **OntologyTermName**: ontology term
    - **OntologyTermDescription**: short HI description of the ontology term as defined in the relevant ontology
    - **OntologyName**: The name of the ontology in which the term is defined
    - **OntologyTermID**: This is a MR element
    - **OntologyTermURL**: This provides the link to the ontology term through a persistent identifier
    - **OntologyTermQuality**: This provides information on how well the ontology term fits the metadata field

If the data type is enumeration, then there is a controlled vocabulary linked to that field

- **ControlledVocabulary**: This is a compound element providing the description of the controlled vocabulary
    - **VocabularyElementID**: element identifier of a unique element of the controlled vocabulary
    - **VocabularyElementDescription**: description of the element
    - **OntologyTerm**: element identifier is a compound field consisting of several sub-elements. For their description see above.
        - **OntologyTermName**
        - **OntologyTermDescription**
        - **OntologyName**
        - **OntologyTermID**
        - **OntologyTermURL**
        - **OntologyTermQuality**

We can therefore describe the elements of the metadata-metadata in the same terms as well, albeit that these may contain different elements depending on the schema. In the end we can describe the elements of the metadata-metadata-metadata in terms of themselves which then becomes the basis for the description of any metadata schema.

This is a standardized approach to describing metadata, in other words a standard metadata of metadata (data dictionaries). Because it can describe any metadata field in a standardized way, the schema is both flexible and standardized.

Self-Describing Metadata

So, at the highest level of abstraction, we have a metadata schema that describes itself. We can use this schema to describe any metadata of metadata schemas that may contain additional elements. It is more intuitive and more self-contained than for instance the RDF schema (Dan Brickley and Guha, 2014). Besides describing the OIMS metadata schema, the self-describing OIMS schema can also be used to describe any other metadata schema. Besides describing already existing data dictionaries, OIMS can be used to describe for instance data entities and their relationships as well as ETL procedures.

In addition to the eight attribute attributes there is one more that we use, namely the attribute "//" in our JSON files which we use as a comment. This allows us to add user friendly information that is not needed by a machine parsing the metadata file.

For ontology terms we have mostly used the very complete and comprehensive NCI Thesaurus OBO Edition (http://www.obofoundry.org/ontology/ncit.html) accessed through the EMBL-EBI ontology look-up service (https://www.ebi.ac.uk/ols/index). In the OIMS approach multiple ontology terms can be attached to an attribute and this is expected to happen in next versions.

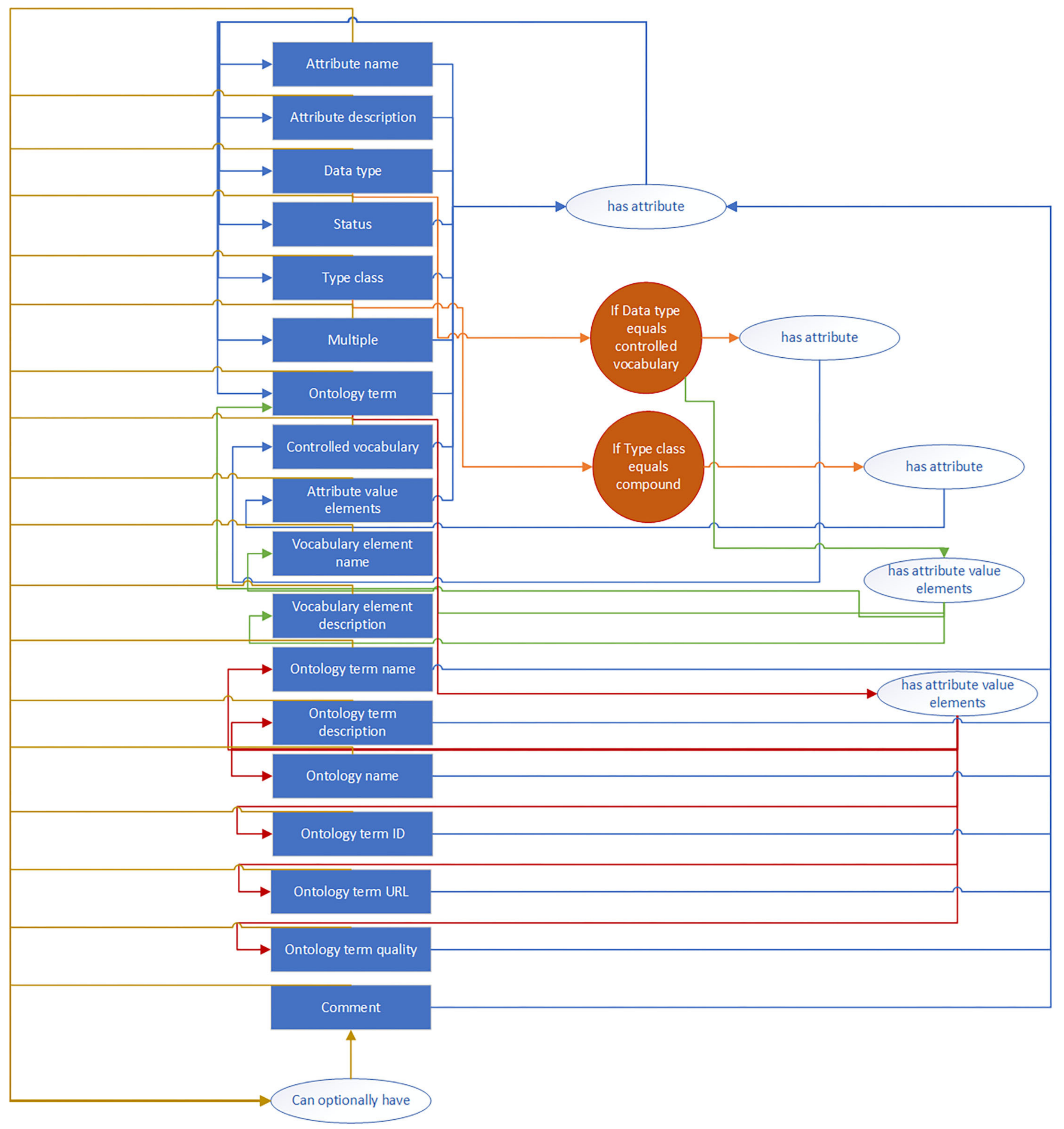

FIGURE 2 | Diagram of the self-describing metadata schema.

In the next subsections we provide a description of each of the elements of the self-describing metadata schema. For the description of the schema in JSON format, see the **Supplementary Material**: "data sheet 1.docx." In **Figure 2** we see a schematic diagram of the self-describing metadata schema.

The description of the self-describing metadata is purposely done in a way that closely resembles the structured format underlying the schema instead of a more narrative-like approach. The importance is to provide the definitions of all the elements as highlighted in **Figure 2**.

The diagram in **Figure 2** demonstrates that each attribute in the blue boxes has at least the first seven attributes. The attribute data type can have the value "controlled vocabulary." In that case an additional attribute is needed to describe the controlled vocabulary. It has the specific attribute value elements linked to controlled vocabulary as well as the more general attribute ontology term. Ontology terms have specific attribute value elements as well-related to ontology terms. These are two examples of compound attributes and hence they have the related attribute that captures these compound elements. Note that this schema is somewhat different from a standard database schema. It defines everything that can then be used in the metadata schemas describing actual data.

Attribute Name

Take for instance the concept **AttributeName**. It can be described in terms of the major attributes:

- **AttributeName = AttributeName**
- **AttributeDescription =** the name of a metadata field
- **DataType** = simple character string
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = false
- **OntologyTerm** =
    - **OntologyTermName**: Name
    - **OntologyTermDescription**: The words or language units by which a thing is known
    - **OntologyName:** NCIT
    - **OntologyTermID**: C42614
    - **OntologyTermUR**: http://purl.obolibrary.org/obo/NCIT_C42614
    - **OntologyTermQuality**: to be confirmed

Attribute Description

In a similar vein, **AttributeDescription** can be described in terms of the major attributes:

- **AttributeName = AttributeDescription**
- **AttributeDescription =** Description of a metadata field
- **DataType** = character string
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = false
- **OntologyTerm** = combination of:
    - **OntologyTermName**: Description
    - **OntologyTermDescription**: A written or verbal account, representation, statement, or explanation of something.
    - **OntologyName:** NCIT
    - **OntologyTermID**: C25365
    - **OntologyTermUR**: http://purl.obolibrary.org/obo/NCIT_C25365
    - **OntologyTermQuality**: to be confirmed.

Data Type

DataType is a bit more complex as it has a controlled vocabulary that needs to be defined. It can be described as:

- **AttributeName = DataType**
- **AttributeDescription =** The datatypes of the various fields of the self-describing metadata schema
- **DataType** = Controlled vocabulary
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = true
- **ControlledVocabulary** = a set of unique elements containing
    - Simple character string defined as
        - **VocabularyElementID**: Simple character string
        - **VocabularyElementDescription**: simple machine-readable language independent sequence of characters
        - **OntologyTerm**:
            - **OntologyTermName**: Simple Character String Data Type
            - **OntologyTermDescription**: A data type comprised of a text string that can be displayed, or machine processed, and which has no language.
            - **OntologyName:** NCIT
            - **OntologyTermID:** C95682
            - **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C95682
            - **OntologyTermQuality**: to be confirmed
    - String defined as
        - **VocabularyElementID**: String
        - **VocabularyElementDescription**: An expression consisting of a linear sequence of symbols (characters or words or phrases).
        - **OntologyTerm**:
            - **OntologyTermName**: String
            - **OntologyTermDescription**: An expression consisting of a linear sequence of symbols (characters or words or phrases).
            - **OntologyName:** NCIT
            - **OntologyTermID**: C45253
            - **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C45253
            - **OntologyTermQuality**: to be confirmed
    - Boolean defined as
        - **VocabularyElementID**: Boolean
        - **VocabularyElementDescription**: The type of an expression with two possible values, "true" and "false."
        - **OntologyTerm**:
            - **OntologyTermName**: Boolean
            - **OntologyTermDescription**: The type of an expression with two possible values, "true" and "false."
            - **OntologyName:** NCIT
            - **OntologyTermID:** C45254
            - **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C45254
            - **OntologyTermQuality**: exact

- Controlled vocabulary defined as
  - **VocabularyElementID**: Controlled vocabulary
  - **VocabularyElementDescription**: set of unique elements that are the only valid values of a variable, also known as enumeration or in R terminology a factor.
  - **OntologyTerm**:
    - **OntologyTermName**: Controlled vocabulary
    - **OntologyTermDescription**: A set of terms that are selected and defined based on the requirements set out by the user group, usually a set of vocabulary is chosen to promote consistency across data collection projects.
    - **OntologyName:** NCIT
    - **OntologyTermID**: C25704
    - **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C25704
    - **OntologyTermQuality**: to be confirmed
- Text defined as
  - **VocabularyElementID**: Text
  - **VocabularyElementDescription**: sequence of strings
  - **OntologyTerm**:
    - **OntologyTermName**: Text
    - **OntologyTermDescription**: The words of something written.
    - **OntologyName:** NCIT
    - **OntologyTermID**: C25704
    - **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C25704
    - **OntologyTermQuality**: to be confirmed
- HTML defined as
  - **VocabularyElementID**: HTML
  - **VocabularyElementDescription**: Hypertext Markup Language
  - **OntologyTerm**:
  - **OntologyTermName**: Hypertext Markup Language
    - **OntologyTermDescription**: A standard markup language used to display content on a web page, as specified by the World Wide Web Consortium (W3C).
    - **OntologyName:** NCIT
    - **OntologyTermID:** C142380
    - **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C142380
    - **OntologyTermQuality**: to be confirmed
- Compound
  - **VocabularyElementID**: compound
  - **VocabularyElementDescription**: the datatype of the attribute is an array of elements possibly but not necessarily with different datatype combinations
  - **OntologyTerm**: no ontology term available

- **OntologyTerm** = combination of
  - **OntologyTermName**: DataType
  - **OntologyTermDescription**: An indication of the form that a value will have.
  - **OntologyName:** NCIT
  - **OntologyTermID**: C42645
  - **OntologyTermUR**: http://purl.obolibrary.org/obo/NCIT_C42645
  - **OntologyTermQuality**: to be confirmed

Note that the controlled vocabulary contains only the data types needed to describe the self-describing metadata schema.

Status

The attribute **Status** is complex as it has a controlled vocabulary that needs to be defined. It can be described as follows:

- **AttributeName = Status**
- **AttributeDescription =** identification if a metadata field is either: required; recommended; required if applicable; recommended if applicable; optional
- **DataType** = Controlled vocabulary
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE
- **ControlledVocabulary** = a set of unique elements containing
  - required
    - **VocabularyElementID**: required
    - **VocabularyElementDescription**: indication if the attribute is mandatory
    - **OntologyTerm**:
      - **OntologyTermName**: Required Indicator
      - **OntologyTermDescription**: An indication as to whether entity is mandatory.
      - **OntologyName:** NCIT
      - **OntologyTermID:** C164599
      - **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C164599
      - **OntologyTermQuality**: to be confirmed
  - recommended
    - **VocabularyElementID**: recommended
    - **VocabularyElementDescription**: indication as to whether attribute is not mandatory but recommended
    - **OntologyTerm**: no ontology term available
  - required if applicable
    - **VocabularyElementID**: required if applicable
    - **VocabularyElementDescription**: required if applicable
    - **OntologyTerm**: no ontology term available

- ○ Recommended if applicable
  - ■ **VocabularyElementID**: recommended if applicable
  - ■ **VocabularyElementDescription**: recommended if applicable
  - ■ **OntologyTerm**: no ontology term available
- ○ Optional
  - ■ **VocabularyElementID**: Optional
  - ■ **VocabularyElementDescription**: optional attribute of a metadata field
  - ■ **OntologyTerm**:
    - **OntologyTermName**: Optional
    - **OntologyTermDescription**: Possible but not necessary; left to personal choice.
    - **OntologyName:** NCIT
    - **OntologyTermID**: C25603
    - **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C25603
    - **OntologyTermQuality**: to be confirmed
- **OntologyTerm** = no ontology term available

Note that some of the ontology terms are missing for this attribute. This does not imply that this is a new term. It is used in the JSON metadata file of DataVerse (https://dataverse.org/), an open access data repository system commonly used for international agricultural research for development.

Type Class

The attribute type class can be described as follows:

- **AttributeName = TypeClass**
- **AttributeDescription =** if the attribute is compound or primitive
- **DataType** = Controlled vocabulary
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE
- **ControlledVocabulary** = a set of unique elements containing
  - ○ primitive
    - ■ **VocabularyElementID**: primitive
    - ■ **VocabularyElementDescription**: the attribute does not have underlying attributes
    - ■ **OntologyTerm**: no ontology term available
  - ○ compound
    - ■ **VocabularyElementID**: compound
    - ■ **VocabularyElementDescription**: the attribute has underlying attributes
    - ■ **OntologyTerm**: no ontology term available
- **OntologyTerm** = no ontology term available

Note that some of the ontology terms are missing for this attribute. This does not imply that this is a new term. It is used in the JSON metadata file of DataVerse (https://dataverse.org/).

Multiple

The attribute multiple can be described as:

- **AttributeName = Multiple**
- **AttributeDescription =** can the attribute have multiple values
- **DataType** = Boolean
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE
- **OntologyTerm** = combination of
  - ○ **OntologyTermName**: Multiple
  - ○ **OntologyTermDescription**: Having, relating to, or consisting of more than one individual, element, part, or other component; manifold.
  - ○ **OntologyName:** NCIT
  - ○ **OntologyTermID**: C17648
  - ○ **OntologyTermUR**: http://purl.obolibrary.org/obo/NCIT_C17648
  - ○ **OntologyTermQuality**: to be confirmed

This attribute is also used in the JSON metadata file of DataVerse (https://dataverse.org/).

Controlled Vocabulary

Controlled vocabulary is the code book of a specific controlled vocabulary used in an attribute. It is linked to the data type Controlled Vocabulary. It is an array of values that have multiple attributes themselves.

The attribute, controlled vocabulary, can be described as:

- **AttributeName = ControlledVocabulary**
- **AttributeDescription =** controlled vocabulary definition if data type is controlled vocabulary also known as an enumeration or a factor in R.
- **DataType** = Compound
- **Status** = required if applicable
- **TypeClass** = compound
- **Multiple** = TRUE
- **AttributeValueElements** = when a data type is compound the array elements of the compound data type must be described:
  - ■ **VocabularyElementName**
  - ■ **VocabularyElementDescription**
  - ■ **OntologyTerm**
- **OntologyTerm** = combination of
  - ○ **OntologyTermName**: Controlled vocabulary
  - ○ **OntologyTermDescription**: A set of terms that are selected and defined based on the requirements set out by the user group, usually a set of vocabulary is chosen to promote consistency across data collection projects.
  - ○ **OntologyName:** NCIT
  - ○ **OntologyTermID**: C25704
  - ○ **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C25704
  - ○ **OntologyTermQuality**: to be confirmed

Vocabulary Element Name
The specific attribute value elements linked to the compound data type of a controlled vocabulary include the identifier of a controlled vocabulary element

- **AttributeName = VocabularyElementName**
- **AttributeDescription =** the element identifier in a controlled vocabulary
- **DataType** = simple character string
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE
- **OntologyTerm** = no ontology term available

Vocabulary Element Description
The specific attribute value elements linked to the compound data type of a controlled vocabulary include the description of a controlled vocabulary element

- **AttributeName = VocabularyElementDescription**
- **AttributeDescription =** the description of an element in a controlled vocabulary in human-intelligible terms
- **DataType** = text
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE
- **OntologyTerm** = no ontology term available

Ontology Term
Ontology term is described elsewhere in section Structure of OIMS. However, ontology term in the context of a controlled vocabulary has a special significance. Ontologies are as said before the formalization of knowledge at a conceptual level. When dealing with the variable names, ontology terms provide the conceptual basis for semantic interoperability. When dealing with the values of the variables, many alternative classifications exist and are used. The lack of standardization hinders interoperability. To improve interoperability various classifications of possible values can be mapped onto each other creating the basis for interoperability of actual data. The details of the processes and procedures related to the creation of such concordances goes beyond the scope of the current paper.

Ontology Terms

Ontology terms can be added for semantic interoperability. Modern data portals such as GARDIAN (https://gardian.bigdata.cgiar.org/), rely on formalized ontology terms for enhanced data interoperability. An ontology is a formal representation of a body of knowledge within a given domain. Ontologies usually consist of a set of classes (or terms or concepts) with relations that operate between them.

Ontology terms can be described as:

- **AttributeName = OntologyTerm**
- **AttributeDescription**: the ontology term for the relevant attribute
- **DataType** = compound
- **Status** = recommended
- **TypeClass** = compound
- **Multiple** = TRUE
- **AttributeValueElements** = when a data type is compound the array elements of the compound data type must be described:
    - **OntologyTermName**
    - **OntologyTermDescription**
    - **OntologyName**
    - **OntologyTermID**
    - **OntologyURL**
    - **OntologyTermQuality**
- **OntologyTerm** = combination of
    - **OntologyTermName**: Ontology term
    - **OntologyTermDescription**: A term (name) from an ontology
    - **OntologyName:** EDAM
    - **OntologyTermID**: data:0966
    - **OntologyTermURL**: http://edamontology.org/data_0966
    - **OntologyTermQuality**: to be confirmed **Or**
    - **OntologyTermName**: Ontology concept
    - **OntologyTermDescription**: A unique entry or term in a specific ontology
    - **OntologyName:** NCIT
    - **OntologyTermID**: C89273
    - **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C89273
    - **OntologyTermQuality**: to be confirmed

Note that we provide two ontology terms for the attribute ontology term.

Ontology Term Name
The attribute OntologyTermName which is part of the compound datatype of the value of an ontology term can be described as:

- **AttributeName = OntologyTermName**
- **AttributeDescription**: the identifier of an ontology term for the relevant attribute
- **DataType** = simple character string
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE
- **OntologyTerm** = no ontology term available

Ontology Term Description
The attribute OntologyTermDescription which is part of the compound datatype of the value of an ontology term can be described as:

- **AttributeName = OntologyTermDescription**
- **AttributeDescription**: the description of an ontology term for the relevant attribute in human-intelligible terms
- **DataType** = text
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE

- **OntologyTerm** = no ontology term available

Ontology Name
The attribute OntologyName which is part of the compound datatype of the value of an ontology term can be described as:

- **AttributeName = OntologyName**
- **AttributeDescription**: the name of the ontology that describes the ontology term
- **DataType** = simple character string
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE
- **OntologyTerm** = no ontology term available

Ontology Term Identifier
The attribute OntologyTermIdentifier which is part of the compound datatype of the value of an ontology term can be described as:

- **AttributeName = OntologyTermIdentifier**
- **AttributeDescription**: the unique identifier for the term within the ontology
- **DataType** = simple character string
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE
- **OntologyTerm** = no ontology term available

Ontology URL
The attribute OntologyURL which is part of the compound datatype of the value of an ontology term can be described as:

- **AttributeName = OntologyURL**
- **AttributeDescription =** persistent URI of the ontology term
- **DataType** = HTML
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE
- **OntologyTerm** = no ontology term available

Ontology Term Quality
The attribute OntologyTermQuality which is part of the compound datatype of the value of an ontology term can be described as:

- **AttributeName = OntologyTermQuality**
- **AttributeDescription**: the degree to which the ontology term covers the attribute
- **DataType** = controlled vocabulary
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = FALSE
- **ControlledVocabulary**
    - Exact match
        - **VocabularyElementID**: exact match
        - **VocabularyElementDescription**: the ontology terms match the attribute exactly
        - **OntologyTerm**: no ontology term available
    - To be confirmed
        - **VocabularyElementID**: to be confirmed
        - **VocabularyElementDescription**: the quality of the ontology term in describing the attribute needs to be confirmed
        - **OntologyTerm**: no ontology term available
- **OntologyTerm** = no ontology term available

Attribute Value Elements
When a data type is compound the array elements of the compound data type must be described. The attribute AttributeValueElements provides that list. And can formally be described as:

- **AttributeName = AttributeValueElements**
- **AttributeDescription**: Attributes that are part of a compound attribute
- **DataType** = simple character string
- **Status** = required
- **TypeClass** = primitive
- **Multiple** = TRUE

Comment
As we mentioned earlier, we include a comment attribute. This allows us to add comments to improve transparency and understandability of metadata files. When parsing the JSON file, comments can be skipped by the machine reading the metadata.

- **AttributeName = //**
- **AttributeDescription**: comment
- **DataType** = text
- **Status** = optional
- **TypeClass** = primitive
- **Multiple** = TRUE
- **OntologyTerm** = combination of
    - **OntologyTermName**: comment
    - **OntologyTermDescription**: A written explanation, observation or criticism added to textual material.
    - **OntologyName:** NCIT
    - **OntologyTermID**: C25393
    - **OntologyTermURL**: http://purl.obolibrary.org/obo/NCIT_C25393
    - **OntologyTermQuality**: exact match

EXAMPLE USING OIMS TO DESCRIBE A DATA FILE

Stepwise Description of Data and Metadata
As an example, we use a small section from a household survey file containing household rosters identifying household composition and household member characteristics, see **Figure 3** for a screenshot from STATA data viewer.

We observe the following variables:

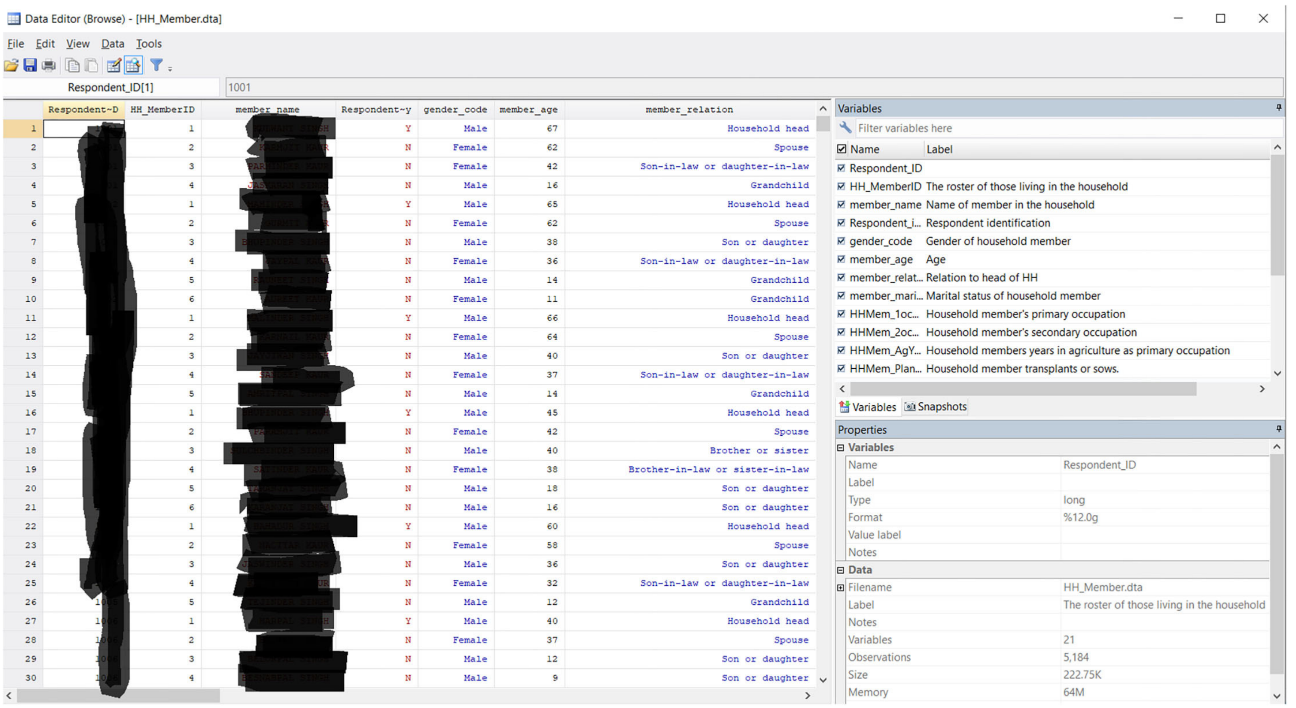

FIGURE 3 | Screen shot of an example data file of household composition. Personally identifiable information has been blacked out.

```
                 storage   display    value
variable name    type      format     label      variable label

Respondent_ID    long      %12.0g
HH_MemberID      byte      %8.0g                 The roster of those living in the
                                                   household
member_name      str21     %21s                  Name of member in the household
Respondent_id~y  str1      %9s                   Respondent identification
gender_code      byte      %8.0g      L_Gender   Gender of household member
member_age       byte      %8.0g                 Age
member_relation  byte      %41.0g     L_HH_Relation
                                                 Relation to head of HH

L_HH_Relation:
           1 Household head
           2 Spouse
           3 Son or daughter
           4 Grandchild
           5 Father or mother
           6 Brother or sister
           7 Nephew or niece
           8 Uncle or aunt
           9 Son-in-law or daughter-in-law
          10 Father-in-law or mother-in-law
          11 Brother-in-law or sister-in-law
          12 Grandparent
          13 Other relative of head or spouse
          14 Servent (farm worker, herder, maid, etc.)
          15 Other unrelated person
L_Gender:
           1 Male
           2 Female
```

FIGURE 4 | Extractable metadata from STATA.

- Household_ID
- HH_memberID
- Member_name
- Respondent_identity
- Gender_code
- Member_age
- Member_relation

The STATA file itself already contains some key metadata (see **Figure 4**):

- VariableName
- VariableDescription
- DataType
- Format

Moreover, extracting the metadata from the STATA file allows us to create a list of the elements of enumerations. However, these enumerations are locally defined classifications that do not necessarily have a relationship with some standard classification.

To enhance the reusability of the data CIMMYT, the holder of this particular dataset, is encouraging tagging data with rich metadata including but not limited to:

- Key: whether a variable is a primary key, foreign key, or a regular variable. A primary key is used to ensure data in the specific column is unique. A foreign key is a column or group of columns in a relational database table that provides a link between data in two tables. It uniquely identifies a record in the relational database table. Only one primary key is allowed in a table.

TABLE 1 | Data dictionary of single primitive fields and simple enumerations.

Variable in the dataset	Metadata field	Value
Household_ID	VariableName	Household_ID
	VariableDescription	Unique identifier of the household in the survey
	DataType	Long integer
	Format	12 characters
	Key	2
	Unit of measurement	NA
	Method of measurement	NA
	Sensitivity	NA
HH_memberID	VariableName	HH_memberID
	VariableDescription	Unique identifier of the household member within a household
	DataType	Integer
	Format	8 characters
	Key	0
	Unit of measurement	NA
	Method of measurement	NA
	Sensitivity	NA
Member_name	VariableName	Member_name
	VariableDescription	Name of the household member
	DataType	String
	Format	21 characters
	Key	0
	Unit of measurement	NA
	Method of measurement	Interview
	Sensitivity	PII
Respondent_ identity	VariableName	Respondent_identity
	VariableDescription	Is this the household head
	DataType	Enumeration
	Enumeration	Y = respondent N = other household member
	Format	9 characters
	Key	0
	Unit of measurement	NA
	Method of measurement	Interview
	Sensitivity	No
Gender_code	VariableName	Gender_code
	VariableDescription	Gender of the household member
	DataType	Enumeration
	Enumeration	Male Female
	Format	8 characters
	Key	0
	Unit of measurement	NA
	Method of measurement	Interview
	Sensitivity	Indirect PII
Member_age	VariableName	Member_age
	VariableDescription	Age of household member
	DataType	Numeric
	Format	8 characters
	Key	0
	Unit of measurement	Years
	Method of measurement	Interview
	Sensitivity	Indirect PII
Member_relation	VariableName	Member_relation
	VariableDescription	Relation to the household head
	DataType	Enumeration
	Format	41 characters
	Key	0
	Unit of measurement	NA
	Method of measurement	Interview
	Sensitivity	Indirect PII

- Unit of measurement
- Method of measurement
- Sensitivity of the data

The data dictionary for these seven variables therefore contains seven primitive fields and a complex one for defining any controlled vocabularies. For the description of the schema in JSON format, see the **Supplementary Material**: "data sheet 2.docx."

Note that this table does not file does not contain a primary key. Instead, a primary key can be constructed by combining the household ID and the HH member ID. There is one variable containing pure personally identifiable information, namely the name of the household member. By any ethics standard that data cannot be made public. Granular household member characteristics such as gender age education levels, marital status, and occupation can be used to reidentify households hence they are considered indirect PII that can only be made public in aggregated form. Information on data sensitivity can be added to the structural metadata of a data file.

In this example the method of measurement is interview. When collecting information about past events, such as crop yield, it can be more appropriate to use recall as the method of measurement. If actual measurements were taken such as crop cuts, this can be indicated.

Separate tables need to be provided with the code books in machine readable form.

Obviously, we can expand this data dictionary with any number of relevant metadata fields that are appropriate for the context. For the purpose of explaining OIMS we limit ourselves to these key fields. We now take a closer look at the fields in the data dictionary. For the description of the schema in JSON format, see the **Supplementary Material**: "data sheet 3.docx."

The metadata of this metadata can be readily described in terms of the self-describing metadata schema highlighted in section Self-Describing Metadata. For the description of the

```
{"Metadata Content":[
   {
    "VariableName":"Household_ID",
    "VariableDescription":"Unique identifier of the household in the survey",
    "Datatype":"Long integer",
    "Format":"12 characters",
    "Key":"2",
   },
   {
    "VariableName":"HH_memberID",
    "VariableDescription":"Unique identifier of the household member within a household",
    "Datatype":"integer",
    "Format":"8 characters",
    "Key":"0",
   },
   {
    "VariableName":"Member_name",
    "VariableDescription":"Name of the household member",
    "Datatype":"String",
    "Format":"21 characters",
    "Key":"0",
    "MethodOfMeasurement":"interview",
    "Sensitivity":"PII"
   },
   {
    "VariableName":"Respondent_identity",
    "VariableDescription":"Is this the household head?",
    "Datatype":"Controlled vocabulary",
    "Format":"9 characters",
    "ControlledVocabulary": [
       {
        "ControlledVocabularyItem":"yes",
        "ControlledVocabularyItemDescription":"yes",
       },
       {
        "ControlledVocabularyItem":"no",
        "ControlledVocabularyItemDescription":"no",
       }
      ]
    "Key":"0",
    "MethodOfMeasurement":"interview",
    "Sensitivity"="none"
   }
```


FIGURE 5 | Portion of the JSON file containing the data dictionary in OIMS format.

schema in JSON format, see the **Supplementary Material**: "data sheet 4.docx."

Turning the Information Into Machine Readable Form

Turning the example into a machine readable JSON format requires three steps. The first step is formalizing the information in each table into JSON format. The second step is the provision of a header into the JSON file. The header is crucial as it provides the information where the metadata structure can be found. The third step is creating a parent-child relationship table that links data files in a dataset.

Basic Transformation of Metadata Into JSON Format

The JSON format as highlighted in section Metadata Schema Format is a flexible standard for data exchange across platforms and systems.

The information in **Table 1** can therefore be transformed into JSON format. In **Figure 5** we see a portion of that transformed table (see **Supplementary Material** for the full JSON file: ExampleDataDictionary.JSON).

In a similar vein, the information in the description of the data dictionary found in **Table 2** can be transformed into JSON format (see **Supplementary Material** for the full JSON file: ExampleDataDictionaryMetadata.JSON). In the example, we purposefully did not use the exact same terminology as in the self-describing schema at the highest level of abstraction. This implies that we need one additional metadata file that links the terminology used in the data dictionary metadata to the standard OIMS terminology (see **Supplementary Material** for the full JSON file: ExampleDataDictionaryMetadata2OIMS.JSON). This has the added benefit of being able to define specifically all relevant elements such as data types that may be specific for a given dataset or metadata schema.

Obviously, the self-describing metadata schema presented in section Self-Describing Metadata is also available in JSON format (see **Supplementary Material** for the full JSON file: OIMS_vers.JSON).

Adding a Header to the JSON File

The header in any OIMS JSON file provides crucial information to place the metadata file in context. The header should contain the following information.

- Name of the metadata file
- Version of the metadata
  - Version identifier
  - Version status: is it under development, review, restricted or openly available
- Metadata schema used
  - Schema name
  - Schema type: this field can have multiple elements depending on the complexity of the metadata schema including:
    - Technical metadata
    - Descriptive metadata
    - Structural metadata
    - Entity metadata
  - Schema version
  - Schema URL
  - URI to schema documentation

Ideally the header should also contain some descriptive information on the creator, the affiliation and some contact details so interested users can get in touch.

Data Entities and Parent-Child Relationships

This paper does not deal in detail with the way the data entities are managed in terms of metadata within the context of the OIMS metadata philosophy. A separate paper on this topic is in preparation. For interoperability of datasets, it is essential, and it builds on the concepts laid out in this paper. Key element in the use of data entities in conjunction with OIMS are the parent-child relationships that exist. Datasets have one or more files containing data. These data files have associated metadata files as well as **Supplementary Material**. The data entity approach enhances data interoperability through the structuring this type of information and storing it in a way compatible with the OIMS metadata schema.

TABLE 2 | Metadata of the data dictionary.

Metadata field	Attributes	Value
VariableName	MetadataFieldName	VariableName
	MetadataFieldDescription	The name of the variable
	DataType	Simple character string
	Format	Alphanumeric
	Status	Required
	TypeClass	Primitive
	Multiple	FALSE
VariableDescription	MetadataFieldName	VariableDescription
	MetadataFieldDescription	Description of the variable: Label in STATA
	DataType	String
	Format	Alphanumeric
	Status	Required
	TypeClass	Primitive
	Multiple	FALSE
DataType	MetadataFieldName	DataType
	MetadataFieldDescription	The datatypes of the various fields of the variables
	DataType	Enumeration
	Status	Required
	TypeClass	Primitive
	Multiple	FALSE
Format	MetadataFieldName	Format
	MetadataFieldDescription	Any specific information about the format of the values in the variable
	DataType	Various
	Status	Required
	TypeClass	Primitive
	Multiple	FALSE
Key	MetadataFieldName	Key
	MetadataFieldDescription	Indicates whether a variable is a primary key, foreign key, or a regular variable. A primary key is used to ensure data in the specific column is unique. A foreign key is a column or group of columns in a relational database table that provides a link between data in two tables. It uniquely identifies a record in the relational database table. Only one primary key is allowed in a table.
	DataType	Enumeration
	enumeration	0 = not a key, regular variable 1 = primary key 2 = foreign key
	Status	Required
	TypeClass	Primitive
	Multiple	FALSE
Unit of measurement	MetadataFieldName	Unit of Measurement
	MetadataFieldDescription	Unit of Measurement

(Continued)

TABLE 2 | Continued

Metadata field	Attributes	Value
	DataType	Enumeration
	Status	Required if appropriate
	TypeClass	Primitive
	Multiple	FALSE
Method of measurement	MetadataFieldName	Method of measurement
	MetadataFieldDescription	How the value of the variable was determined
	DataType	Enumeration
	Status	Required if appropriate
	TypeClass	Primitive
	Multiple	FALSE
Sensitivity	MetadataFieldName	Sensitivity
	MetadataFieldDescription	Information on the sensitivity of the information in the variable related to personally identifiable information, granular geo-spatial coordinates and or sensitive questions
	DataType	Enumeration
	Enumeration	PII Indirect PII NA = not applicable GPS = granular Geospatial information
	Status	Required if appropriate
	TypeClass	primitive
	Multiple	FALSE

DISCUSSION, CONCLUSIONS, AND NEXT STEPS

This paper presented an internally consistent approach to providing metadata for data files when standards are missing. The approach is flexible and extensible so it will not be obsolete before it is implemented at scale. The approach is based on the concept of data lakes where data is stored as is. To ensure that data lakes do not become swamps, metadata is indispensable (Ravat and Zhao, 2019). The OIMS metadata schema approach can help to standardize the description of metadata and thus can be considered the fishing gear to extract data from the data lake. Past approaches have been comprehensive but cumbersome. That could be the reason that for instance DDI is limited to some large-scale data projects.

Currently researchers can collect data which is not compatible (e.g., because questions were phrased differently, or amounts were measured using different methods). A flexible metadata schema like OIMS does not disallow this in contrast to efforts at data standardization. This begs the question whether the development of an incredibly flexible meta-data schema simply facilitate the collection of disparate data sources. Interoperability in general is much better served by data standardization. Many high variety data sets already exist and hence the highly flexible approach of OIMS serves to tag those data sets with metadata in a standardized way. The agile nature of the approach will support the uptake of OIMS.

The example in the paper illustrates the potential of the use of OIMS for making datasets interoperable and hence reusable. We are in the process of tagging several datasets with rich structural metadata and placing that in the OIMS metadata schema, this will be reported on in due time. The proof of the pudding is in the eating. Over the next years, as requirements for interoperability in relation to open and FAIR data are likely to become more stringent, the OIMS metadata schema can be a useful tool. Existing data dictionaries can be described in terms of the OIMS schema without altering the data dictionaries themselves. This implies that datasets themselves also do not need to be changed. The additional information can be provided at a fairly high level of aggregation. The next steps include demonstrating how this schema can be used to link multiple datasets, covering different topics, to use the analogy of a data lake, demonstrate how the schema can be used to fish data from the lake.

In the paper the importance of ontologies as formalized knowledge and relationships within knowledge domains was mentioned. For socio-economic household data a socio-economic ontology is under development, commonly known as SEOnt (Arnaud et al., 2020; Kim et al., under review), that initially links to a set of standardized survey questions, commonly known as 100Q (van Wijk et al., 2019), that builds on the RHOMIS approach (Hammond et al., 2017). SEOnt is a socio-economic ontology of controlled vocabularies, classifications, and concordances that allow standardization of key indicators, including gender-related indicators. The ontology has been developed by CGIAR researchers and collaborators as part of the activities undertaken in the CGIAR Platform for Big data in Agriculture.

In a setting where the data are standardized, there seems less urgency for flexibility in the metadata schema. However, evolving insights on data and its uses, can and should lead to the tagging of existing datasets even if they are based on a standardized format with additional metadata. Hence the flexibility in the metadata schema is useful for highly standardized datasets as well.

For data interoperability in general one can argue that standardization of the data is the most straightforward way of creating interoperability. However, in some domains, such as the social sciences, including economics, standardization is not a realistic option given the high variety of research questions and related data needs. If the data is high variety than the next best way of standardization for enhancing data interoperability is by standardizing metadata schemas. In summary this implies that we strive for standardization where possible and flexibility where necessary.

As part of the on-going work of the community of practice on Socio-economic data of the CGIAR Platform for Big Data in Agriculture, implementation of the OIMS metadata schema approach on datasets that can create indicators highlighted in the 100Q approach with linkages to SEOnt is envisaged. This will provide datasets with enhanced interoperability.

With more and other datasets also using the OIMS approach in the near future, it will become possible to turn what is currently a socio-economic data swamp into a data lake that can provide timely actionable information to support the agri-food systems transformation and support efforts to assist smallholders to generate a living income while staying within planetary boundaries.

Implementing OIMS in practice requires data managers and scientists that collect the data to actively engage in providing the relevant metadata. As mentioned before, some of the metadata can be gleaned from the software solutions the scientists use already. As these are structured metadata, they can be extracted by machines. Often it does require curation by the scientist involved, especially when the software solution does not provide key information that the scientist has at hand but is not documented in a machine-readable way already.

The development of graphic user interfaces (GUIs) and tools to convert existing data dictionaries into OIMS compatible JSON format will enhance the user friendliness of the schema. We will report on the development of these tools separately.

Making data interoperable and accessible offers scope for data reuse. However, this comes with a caveat. Not all data can be reused for all purposes. Messy socio-economic datasets can come with numerous biases, including sampling bias and recall-bias to name a few. Ideally information on these issues should be included in the metadata of the dataset.

Developing standards for reporting such important issues can be helpful and the information can be added to any OIMS compatible metadata schema as the relevant fields can be described flexibly. The standardization of the way metadata is documented is the key to interoperability. It allows for reuse of efforts such as reuse of mappings between different representations and ontologies.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

GK was responsible for all aspects of the manuscript.

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SUPPLEMENTARY MATERIAL

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Can the Right Composition and Diversity of Farmed Species Improve Food Security Among Smallholder Farmers?

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Food security and livelihoods among smallholder farmers in sub-Saharan Africa are often constrained by limited farm resource endowment. It can be difficult to improve resource endowment given barriers such as low land availability and the unaffordability of agricultural inputs, so here we ask whether farmers can gain a better return on their resources through optimizing their farm strategy in terms of the composition and/or diversity of crop and livestock species raised. Our survey of 1,133 smallholder farmers in western Kenya and northern Nigeria, using a modified version of RHoMIS, indicated that different farm strategies were related to differences in food security and farm incomes. In particular, we found that it was possible for farms with a high species richness but low resource endowment to achieve similar or better food security and income outcomes than farms with low species richness and high resource endowment. This indicates strong potential for diversification to improve food security and livelihoods among smallholder farmers. However, further research will be required to prove a causal relationship. We also noted some exceptions to this trend that require investigation: increasing species richness was not beneficial for low-resourced, livestock-focused farmers in western Kenya, and increasing species richness was associated with a decline in dietary diversity in northern Nigeria (due to declines in purchased dietary diversity that outweighed increases in on-farm and other sources of dietary diversity). Similar analyses could be applied to a wider RHoMIS dataset covering a greater diversity of countries and agro-ecological zones to help identify where, and why, different farm strategies result in better or worse outcomes for smallholder farmers.

Keywords: farm diversity, crop diversity, farm composition, resource endowment, food security, dietary diversity, RHoMIS

INTRODUCTION

Achieving food and nutrition security in Africa remains a critical and complex challenge (Van Ittersum et al., 2016; Giller, 2020). In 2019, 19.1% of the population were unable to meet their calorific needs, and this is predicted to rise to 25.7% (or 443 million people) by 2030 if current trends continue. Meanwhile, nearly a billion people in Africa are currently unable to afford a healthy diet, and the effects of the ongoing COVID-19 pandemic are expected to further worsen the situation (FAO, 2020). Resolving food security and nutrition will not be easy, and will require a combination of multiple global and local interdisciplinary actions to address challenges including international and domestic policy barriers, unequal food distribution, low soil fertility, and limited access to farm resources (Foley et al., 2011; Springmann et al., 2018; Giller, 2020).

At the farm scale, interventions to improve food security can target both the resources available to farmers, and how farmers make use of those resources to meet their nutritional needs and generate a livelihood. Previous studies indicate that farm resource endowment, in terms of land and livestock assets and inputs of labor and nutrients to manage these, impose a strong limitation on farm production and consequently food security (Tittonell et al., 2005, 2010). However, access to assets and inputs can be challenging to improve, particularly given intractable factors such as limited land availability (Giller, 2020) and the costs of fertilizers and crop protection products (Pingali, 2012). This raises the question of whether, given a certain level of resource endowment, farmers can achieve better outcomes through different strategies to make use of those resources.

One possibility to improve food security may lie in optimizing the composition and diversity of crop and livestock species raised. In particular, there is substantial agronomic and ecological evidence that increased diversification can positively affect farm productivity, food security, and livelihoods. More diverse on-farm production is often linked to more diverse diets (Jones, 2017; Sibhatu and Qaim, 2018) and increased food security (Waha et al., 2018). Farmed species diversity can also benefit productivity, as different plant species occupy different niches in the agroecosystem, leading to complementarity in space and time. This can increase productivity from a given land area and resource input (Isbell et al., 2017). In particular, legumes can increase the nitrogen and phosphorous availability to cereals, with cereal-legume rotations found to increase cereal yields in sub-Saharan Africa by 41% on average (Franke et al., 2018), while a global meta-analysis by Li et al. (2020) indicated that intercropping could save 16–29% of land and 19–36% of fertilizer compared with monocultures.

Farm species diversity can also suppress weed, pest and disease populations (Storkey et al., 2019). For example, rotating soybean and maize reduced *Striga* damage by 12–15% and increased maize grain yield by 16% in Nigeria (Kamara et al., 2020). Crop diversity has also been found to improve yield stability in warmer, drier climates (Steward et al., 2018), and many minor crops, cultivars and livestock breeds are more resilient to extreme weather than dominant, mainstream commodity crops and livestock (Massawe et al., 2016). Manda et al. (2021) found that participation in both single– and multiple–commodity markets was positively and significantly associated with household income and food security, but the greatest benefits were obtained when farmers participated in multiple-commodity markets by diversifying their crops (mainly maize-legume combinations). Crop diversity at the national scale may also increase employment opportunities (Garibaldi and Pérez-Méndez, 2019).

We hypothesize, therefore, that different farm strategies, in terms of the compositions and diversities of crop and livestock species farmed, may lead to different food security outcomes. However, it is important to consider that farm strategy may also be constrained by economic and environmental pressures. For example, livestock may be prioritized over crops where they confer cultural status, or as a more reliable food source in marginal climates, while mixed farming systems may be preferred where livestock enhance crop production through manure and traction for tillage (Moll, 2005). Resources allocated to crop rather than livestock production can increase where environmental conditions (e.g., length of growing season) are more favorable (Cecchi et al., 2010), or where livestock production is hindered by parasites such as the tsetse fly.

Resource endowment has also been shown to influence farm strategy, both negatively and positively; on one hand, greater resources may facilitate specialization, whilst on the other hand, too few resources may limit farmers to relying on just a few crops. For example, Mellisse et al. (2018) describe an increased preference for annual cash crops on small farms in Ethiopia, where selling higher-value cash crops and purchasing lower-value staples is a more viable route to food sufficiency than producing for on-farm consumption. Wiggins et al. (2011) noted that it was common for farmers across Africa to focus on securing sufficient production of a staple crop before expanding into cash cropping, and Snapp and Fisher (2015) observed that this need to first "fill the maize basket" meant that farmers were more likely to diversify their crops only after achieving a certain level of maize production. In contrast, some poorer farming households retain diversity to meet needs they cannot meet through markets. For example, poorer households in western Kenya retained a higher diversity of tree crops, apparently to meet their own medicinal, nutritional and construction needs, whilst wealthier farmers found it easier to meet these needs through purchased goods (Kindt et al., 2004).

In this study, we explored the relationships between resource endowment, farm strategy and food security outcomes among smallholder farmers in western Kenya and northern Nigeria. Little previous comprehensive research on farm composition and diversity has taken place in these regions. The Atlas of African Agriculture Research and Development describes the selected counties in western Kenya as a combination of "maize mixed" and "highland perennial", and Kano and Kaduna states in Nigeria as "agropastoral," "irrigated," and "cereal-root crop mixed" (Auricht et al., 2014)—useful classifications, but describing broad groups of farms at a coarse resolution. Cecchi et al. (2010) classified all of the study area in Kenya as "mixed farming" (albeit their study had a wider geographic scope and a focus on livestock), again leaving a knowledge gap with regard to a more specific characterization of farm composition and diversity within the region.

A handful of previous studies have explored the relationships between the diversity of farmed species and dietary diversity in western Kenya, but with inconsistent findings. Ng'endo et al.

(2016) found no link between food plant diversity and food security or dietary diversity, while Muthini et al. (2020) found that farmed species diversity did increase dietary diversity, although the number of livestock species was the strongest predictor of dietary diversity. Boedecker et al. (2019) also found in a participatory project that increasing homegardens, poultry-raising and nutrition education did increase dietary diversity in women and children. As noted above, Kindt et al. (2004) suggested tree crop diversity was higher on poorer farms, but as a response to, rather than a cause of, food insecurity and low incomes. To our knowledge, no previous studies explored farmed species diversity and dietary diversity in either Kano or Kaduna in Nigeria.

Given this rather sparse state of knowledge in the current literature, the aim of this study was to characterize different farm strategies in western Kenya and northern Nigeria, and understand whether farm strategy is associated with different food security outcomes within the constraints of the resources available to a farm household (**Figure 1**). Specifically, we ask (i) is farm resource endowment related to farm strategy in terms of the composition and/or species richness of crops and livestock within a farm, and (ii) within the constraints of resource endowment, is farm composition and/or species richness associated with different food security, dietary diversity, and farm incomes? To investigate these relationships, we used the Rural Household Multi-Indicator Survey (RHoMIS) to characterize 1,133 smallholder farms across both countries. RHoMIS allows the acquisition of a set of standardized indicators across diverse agricultural contexts, making it a useful tool to compare results between countries and in the context of the wider literature (Hammond et al., 2017). It is also readily modifiable to address additional study-specific questions.

METHODS

Data Collection

Survey Regions and Household Selection

Household surveys were undertaken in eight counties across two provinces (Western Kenya and Nyanza) of Kenya, and in 14 local government areas (LGA) across two states (Kano and Kaduna) of Nigeria (**Figure 2**). These regions were selected for comparison because of their similarities including the widespread presence of maize as a staple crop (Dixon et al., 2001), and comparable ranges of human population densities (Linard et al., 2012) and livestock densities (Robinson et al., 2014). The exact selection of LGAs in Nigeria was modified in response to logistical and security concerns for the enumerator teams.

Households were selected from a hierarchical sampling frame by first randomly selecting eight electoral wards within each county or five electoral wards within each LGA, and then randomly selecting three villages within each selected ward (where wards contained fewer than three villages, they were omitted from the sampling pool in Kenya, or combined with a neighboring ward in Nigeria). Lists of villages within wards were acquired from local government sources and/or Open Street Map Contributors (2015), and the existence of villages confirmed *via* local contacts. Wards were randomly allocated to enumerator teams following incomplete block designs, with each county (Kenya) surveyed by three different enumerator teams and each LGA (Nigeria) being surveyed by two different enumerator teams, so that each team surveyed three villages within one ward in each day.

When enumerators arrived in the village they asked to be directed toward one "small farm", one "medium farm" and one "large farm" to interview. This stratification strategy ensured a breadth of resource endowment was included in the sampled households, given that farm size is a key indicator of resource endowment, and also avoided biasing the selection toward any notions of diversity or lack thereof. Enumerators rotated small/medium/large farms amongst themselves in each village so that each enumerator visited one farm of each size in each ward, to avoid any biases associated with differences between the enumerators.

Surveys

Surveys were undertaken in the main cropping season in each region in 2019, i.e., in June during the long rains in Kenya and in November during the harvest season in northern Nigeria. Five hundred and seventy-four surveys were completed in Kenya and 559 in Nigeria. We used the Rural Household Multiple Indicator Survey (RHoMIS) tool installed on handheld electronic tablets (Hammond et al., 2017). RHoMIS is a modular, standardized survey designed to collect information on agricultural production, nutrition and poverty among rural households and was chosen for this study due to the possibility to collect data specific to our research questions within the context of internationally recognized and comparable indicators. Careful consideration was made as to the inclusion of questions in the survey in order to collect the evidence required to challenge our hypothesis while ensuring the survey could be completed in a reasonable time with each farmer. The modularity of RHoMIS allowed us to expand the crop section in order to have enough information to fully characterize farm composition and farmed species richness, while retaining other sections to allow us to obtain standardized indicators of a wide range of livelihood indicators to embed our results within the wider literature, such as the Food Insecurity Experience Scale, FIES, and the Household Dietary Diversity Score, HDDS. We did however shorten or exclude some other modules in order to keep the survey duration under 1 h to avoid respondent fatigue. Information on additions and deletions to the standard RHoMIS variables can be found in Section 1 Modifications to RHoMIS for the Purposes of This Study, of the **Supplementary Material**.

Data Analysis

Overview

In this study, we took a typology approach to cluster farms into groups with similar resource endowment (RE) and farm composition (FC). Creating typologies is useful to partition out variation in multiple variables to gain better insight into relationships of interest, and typologies have been widely used in research on smallholder farms, with the specific method of typology generation chosen according to each study's distinct aims (Alvarez et al., 2018; Hammond et al., 2020). Typologies

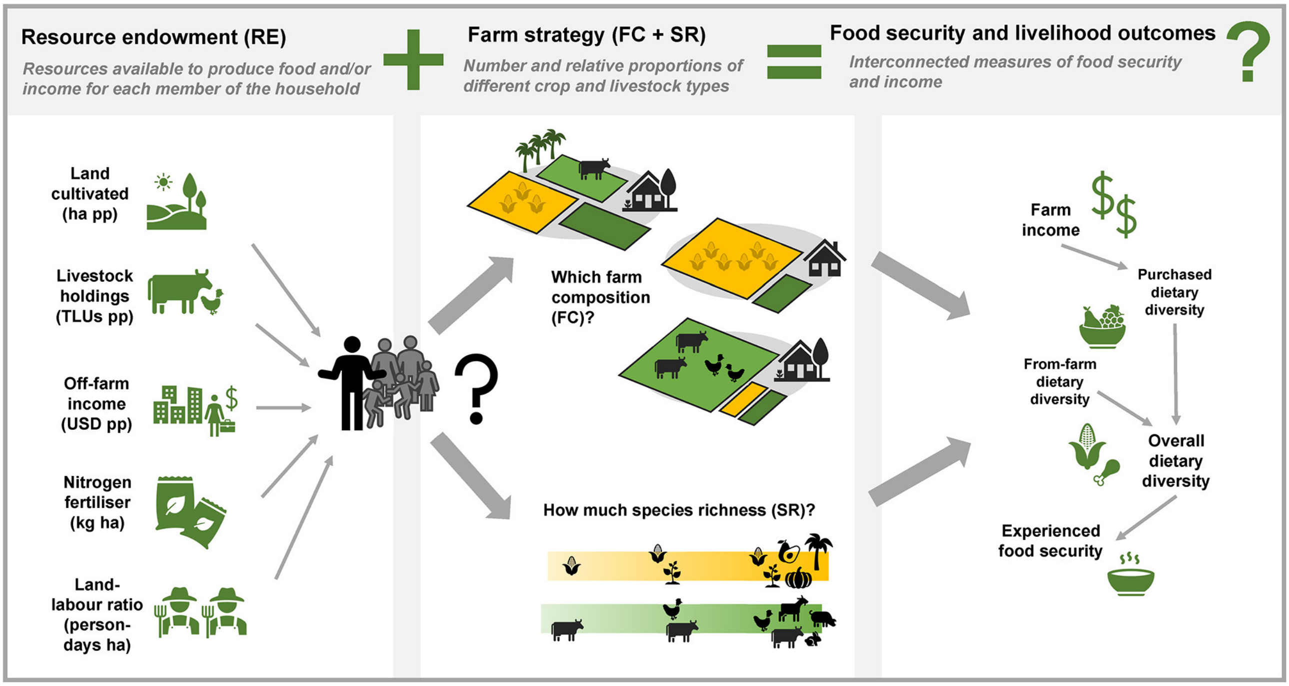

FIGURE 1 | A conceptual framework showing how the different variables considered in this study are related.

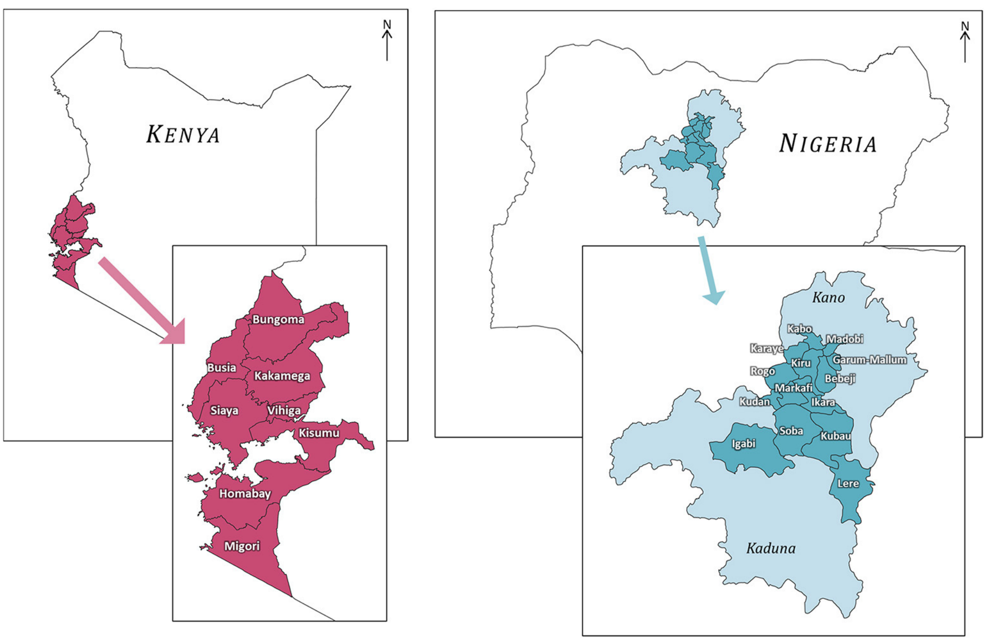

FIGURE 2 | The locations of the counties in Kenya and LGAs in Nigeria in which surveys were undertaken. Different map images are not to scale.

allow multiple potentially correlated variables to be represented as a single variable; for example, wealthier farms are likely to have multiple markers of wealth (more land area, greater livestock holdings, and higher input use), so grouping farms together based on these multiple variables provides an informative indicator of a farm's overall resource endowment. Similarly, a farm that grows a greater proportion of one type of crop is likely to grow smaller proportions of other types of crops, so a typology approach is also useful to classify different farm compositions.

To classify households into different resource endowment typologies we used a hierarchical cluster analysis of variables relevant to resource endowment within our RHoMIS datasets.

The resulting RE classes provided a categorical variable to partition out the variance relating to resource endowment rather than farm strategy in subsequent analyses. Next, we described households' farm strategy according to their farm composition (FC) and farmed species richness (SR). We classified farms into different FC groups using another independent hierarchical cluster analysis of the proportions of different types of crops cultivated and livestock raised on each farm. RE and FC are distinct, independent variables: RE describes total resources available to the household, while FC describes how resources are proportionally distributed among different crop and livestock types. SR is the total number of crop, livestock, and fruit and vegetable species grown on a farm (and is also independent from both RE and FC). We used regression models to explore the effects of RE, FC and SR on outcome variables measuring food security, nutrition, and income (**Figure 1**). All analyses were undertaken in R, version 4.0.3 (R Core Team, 2020).

Resource Endowment Classification

The variables chosen to define resource endowment were land area cultivated (hectares per person), livestock holdings (tropical livestock units, TLUs, per person), off-farm income (Purchasing Power Parity Dollars, USD PPP, per person), N fertilizer (kg ha^{-1} $year^{-1}$) and labor (person-days ha^{-1} $year^{-1}$, including both household labor and hired labor). These variables represent the land and animals available to produce food and income for the household, and the fertilizer, labor, and additional income available to improve their per unit productivity (**Figure 1**). Including the productive assets (land and animals) as well as the means for intensification (fertilizer, labor, off-farm income) is important given that previous studies have identified differences between farms that are constrained by either land or by labor (Tittonell et al., 2010). Our RE variables are similar to variables used in previous research to identify resource endowment groups (e.g., Tittonell et al., 2005, 2010), but are not identical—we excluded variables considered to be food security outcomes for the purpose of this study (see below) and variables for which we did not have suitable data from our survey. Distributions of each variable included are shown in **Supplementary Figure S1**.

Improbable outliers were detected using a combination of the quantile method (where values that are more than two standard deviations away from the mean are identified) and visually inspecting plots of the data (scatter plots and histograms of the data). We identified that many farms in Nigeria had reported unusually high incomes, which was concluded to be a result of the low value of the naira and enumerators accidentally adding extra zeroes (e.g., entering the income from the sale of a cow at 2,000,000 naira rather than 200,000 naira). To address this, incomes were adjusted if the income per unit (head of livestock for each type of animal, liter of milk per animal per day, kilogram of each type of crop yield or annual income per hectare of each type of crop) was unusually high: if over five times the median value for that unit, the income per unit was divided by 10, if over fifty times it was divided by 100 and if over 500 times it was divided by 1,000. This means the value was never reduced to below half the median, but values nearing an order of magnitude (or more) higher than the median were reduced to the same order of magnitude as the median. For example, if the median price for a chicken is 1,000 naira, then entries of 8,000, 80,000, or 800,000 naira were all reduced to 800 naira, while anything up to 5,000 naira was not modified. This adjustment affected the total income estimate for 174 (31%) farms in Nigeria, i.e., the income reported for at least one crop or livestock product on each of these farms was adjusted.

Inexplicable outliers (e.g., a farm reporting 600,000 kg nitrogen fertilizer ha^{-1}) were replaced with "NA" (missing values), and farms were excluded from the cluster analysis if they contained more than one missing value for the resource endowment variables. Thirty-one farms across both countries were excluded for lacking sufficient information.

Farms were classified into different resource endowment (RE) groups according to their relative values of each resource endowment variable using hierarchical cluster analysis, with the Bray-Curtis dissimilarity measure and Ward's clustering method, using R functions *vegan::vegdist* with method = "bray" (Oksanen et al., 2020) and *stats::hclust* with method = "ward.d2" (R Core Team, 2020). Resource endowment variables were scaled prior to the analysis to give them equal weighting in the clustering: each value of the variable was divided by the variable's standard deviation, so that all scaled variables had the same variance (equal to 1). The number of clusters were selected by visually inspecting the dendrogram and assessing the distinctions in crop/livestock proportions at various levels of cluster similarity. This cluster analysis was performed for the farms for each country separately.

Farm Composition Classification and Farmed Species Richness

The survey collected data on the area of land cultivated with each crop and the number of TLUs for different livestock species. Respondents also listed all fruit and vegetables grown, although areas for these were not requested, as fruits and vegetables tend to be grown in homegardens rather than taking up substantial areas of the farm. Participants who grew large areas of a fruit or vegetable, such as bananas or tomatoes, generally reported these as crops. We characterized "farm composition" (FC) by the area dedicated to different types of crops and by the numbers of different livestock species held, while "farmed species richness" (SR) consisted of the total number of all fruit and vegetable, crop, and livestock species grown for home use or sale on the farm. We also considered the number of species in each category on different farms, i.e., the species richness of crops, of livestock, and of fruit and vegetables.

To assign farms to different FC categories, crops were first classified according to their product type or functional group, defined here as: starches (grains and tubers), pulses (legumes), seeds/oils, fruits/vegetables, forage crops (for livestock) and value crops (low in useful calories but higher in income potential: tea, coffee, cotton, sugarcane, chillies etc.). In both Kenya and Nigeria, the occurrence of seeds/oil crops was very low ($<3\%$ farmers) and these crops were primarily sesame, so this category was combined into "value crops" for the purpose of the cluster analysis. Livestock were classified into large animals (ruminants, pigs, equines) and small animals (poultry, rabbits).

To classify farms on the basis of crop and livestock composition, we calculated the proportions of the cultivated land on which each crop was grown, and the proportions of TLUs belonging to either small or large animal species. In order to compare the relative importance of crops and livestock on each farm, the crop and livestock proportions were weighted so that 2 TLUs were equivalent to 1 hectare of cultivated land. 2 TLUs/ha is within the range of the ratios of livestock to cultivated land in the surveyed regions of both countries, lower than the Kenyan median of 2.9 TLUs/ha but higher than the Nigeria median of 0.5 TLUs/ha. This weighting provided an appropriate balance between the contributions of the four crop types and two livestock types in this study; if TLUs/ha was increased (making more animals equivalent to less cropland) then livestock had very little influence on the clustering, and if TLUs/ha was decreased then livestock had an over-large influence on the clustering. Assuming a balanced ratio of crops and livestock was appropriate in this study for testing the hypothesis that overall farm diversity is related to food security and livelihoods. However, the effect of adjusting these ratios could be explored in future analyses focused specifically on the role of livestock or incorporating additional data on their value. The formula for the weighted proportion of a given crop X was thus the proportion of cultivated land planted to the crop (left-hand part of the formula) multiplied by the proportional contribution of cultivated land to the sum of the cultivated land and livestock production asset (right-hand part of the formula):

$$\frac{\textit{land area planted to X}}{\textit{total land area cultivated}} \times \frac{\textit{total land area cultivated}}{(\textit{total TLUs}/2) + \textit{total land area cultivated}}$$

And similarly the formula for the weighted proportion of either small or large TLUs was:

$$\frac{\textit{number of small or large TLUs}}{\textit{total TLUs}} \times \frac{(\textit{total TLUs}/2)}{(\textit{total TLUs}/2) + \textit{total land area cultivated}}$$

The same hierarchical clustering procedure, as described above for resource endowment groups, was used to classify farms into different farm composition (FC) types. Some clusters were manually combined where the clustering algorithm split two groups that were conceptually very similar. For example, if two groups were produced that were distinguished by different amounts of one crop type, yet both groups had more of that crop type than any other group, these two groups would be combined.

Chi-square tests were used to investigate whether there was an association between RE group and FC group within each country, in particular whether farms classified to a particular RE group were more or less likely to be allocated to a particular FC group. ANOVA with type III *F*-tests were used to investigate whether mean SR differed in response to the combination of RE and FC groups to which a farm belonged.

Food Security and Livelihoods

Food security and livelihoods for each household were characterized using the Food Insecurity Experience Scale (FIES) (Cafiero et al., 2018), the number of months that a household was food insecure, the household dietary diversity score (HDDS) (WFP, 2009) in the worst season, and farm income per person per year (**Figure 1**). Distributions of each variable are shown in **Supplementary Figure S2**. For each, a regression model was created for the effects of RE and FC groups, and richness of species farmed (SR). Generalized linear models with a binomial distribution and logit link function were used for bounded outcome variables (i.e., FIES from 0 to 8, HDDS from 0 to 10, and number of food insecure months from 0 to 12) with the response variable specified as counts of "successes" and "failures" (e.g., for HDDS, the number of dietary groups consumed, and the number of dietary groups not consumed). For farm income per person, a linear model with a Normal distribution was used, although income was log transformed to meet assumptions regarding homoscedasticity and Normality in the model residuals (a constant of 1 was added to all income values before transformation to allow inclusion of farms with zero values in the analysis).

For each outcome variable, the full model (all main effects and interactions of RE, FC and SR) was initially fitted. A backward stepwise selection procedure with an AIC selection criterion was then applied to identify an adequate reduced model, with terms dropped from the full model, following the principle of marginality, that most improved the AIC criterion at each step. The statistical significance of all terms remaining in the reduced models, as well as all terms in the full models, were tested using Type III F- or chi-squared tests, as appropriate. Results from both the reduced and full models are presented, as the reduced model enables the correct visual interpretation of the combined effects of the statistically significant terms, while the full models provide an assessment of the relative importance of non-significant terms.

The source of each household's dietary diversity was also explored in terms of the number of food groups produced on farm (farm-based), purchased, and from "free" sources (gathered, exchanged, or gifted). These separate HDDS scores were investigated using the same generalized linear model and variable selection approach as described above.

To assess the robustness of our models, we performed some additional tests. First, we assessed whether there were any correlations between SR and the variables used to create the RE groups, to assess whether any apparent effects of SR could have been driven by intra-cluster correlation between, e.g., land area per person and SR. These correlations are addressed in the results. We also visually assessed plots of model residuals to ensure the models adhered to assumptions of homoscedasticity and Normally-distributed residuals, and Cook's Distance was used to check for outliers exerting undue leverage on the regression (values >1 indicate a problematic point). No issues were detected for either residuals or outliers.

TABLE 1 | Median resources available to farms in each RE group.

Country	RE group	Land cultivated, ha pp*	Labor/land ratio (person-days ha^{-1})	Livestock TLUs pp*	N fertilizer (N kg ha^{-1})	Off-farm income, USD PPP pp*
Kenya	Low	0.10	121.25	0.41	21.50	5.81
	Med	0.18	29.79	0.45	26.88	7.24
	High	0.60	30.36	2.09	7.17	60.96
Nigeria	Low	0.51	12.00	0.25	67.50	82.14
	Med	0.64	17.50	0.41	152.50	34.29
	High	1.37	7.95	0.52	50.73	197.99

*pp, per person, USD PPP pp, international purchasing power parity dollars, per person.

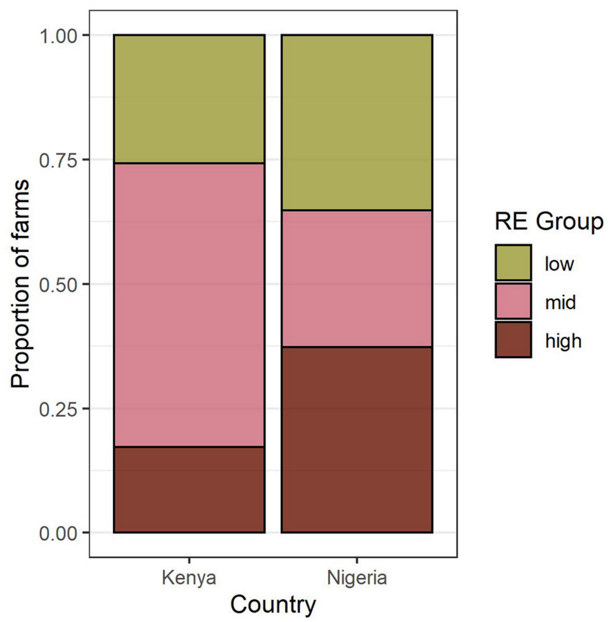

FIGURE 3 | Proportion of farms in each country belonging to each resource endowment (RE) group identified by the cluster analysis.

RESULTS

Resource Endowment

Farms were classified into three resource endowment (RE) groups in each country: "low," "med," and "high" (**Supplementary Figure S3**). Average resource levels and distributions differed between countries (**Table 1**), with Nigerian farms typically larger, receiving more off-farm income, and using more fertilizer, while Kenyan farms had higher labor availability (particularly in the "low" group) and more livestock. In Kenya, more farms belonged to the "med" group, while in Nigeria farms were more likely to be in either the "low" or "high" groups (**Figure 3**).

Farm Composition

Four farm composition groups (FC) were identified for each of Kenya and Nigeria independently using hierarchical cluster analysis (**Supplementary Figure S4**). Groups were named according to the dominant product types. The two countries shared three similar FC groups, described as "cash cropping," "diverse cropping," and "mixed farming", although the median composition in each of these groups did differ somewhat between countries: farms in Nigeria tended to have a greater focus on fewer crop types than in Kenya (**Figure 5**). In Kenya, an additional "livestock dominated" group was identified, and in Nigeria, where maize was dominant in all systems, an additional "starch-cropping" group was identified. In Kenya, the most common FC group was "mixed farming," while in Nigeria it was "starch cropping" (**Figure 4**).

Farms in the livestock dominated group were characterized by a much greater number of livestock compared to the area cultivated than other strategies, while farms in the starch cropping group had a large amount of land dedicated to grains and tubers, with few other crops grown and relatively few livestock raised (**Figure 5**). The cash cropping group comprised farms with a larger than usual proportion of "value" crops, while the diverse cropping and mixed farming strategies were distinguished by relatively lower and higher numbers of livestock, respectively.

The RE group to which a farm belonged did not strongly influence which FC they were allocated to **Table 2**. A chi-square test for Nigeria indicated that similar proportions of each FC group were found in each RE group ($x^2 = 9.15$, d.f. = 6, *P*-value = 0.165). For Kenya, a chi-square test suggest farming strategies were not evenly distributed among RE groups ($x^2 = 38.01$, d.f. = 6, *P*-value $\leq$ 0.001), but **Table 2** indicates that this is largely driven by the "med" RE group having relatively fewer livestock dominated farms and more mixed farming farms compared to both the "low" and "high" RE groups.

Farmed Species Richness

Total species richness (SR) tended to vary more between countries than between FC and RE groups within each country, with a higher mean SR (and greater variance in SR) in Kenya than in Nigeria (**Figure 6**). **Supplementary Figure S5** indicates that the main difference between the two countries was in fruit and vegetable richness, with only small contributions from differences in crop and livestock richness. Median fruit/vegetable richness was 9 in Kenya and 2 in Nigeria, while median crop

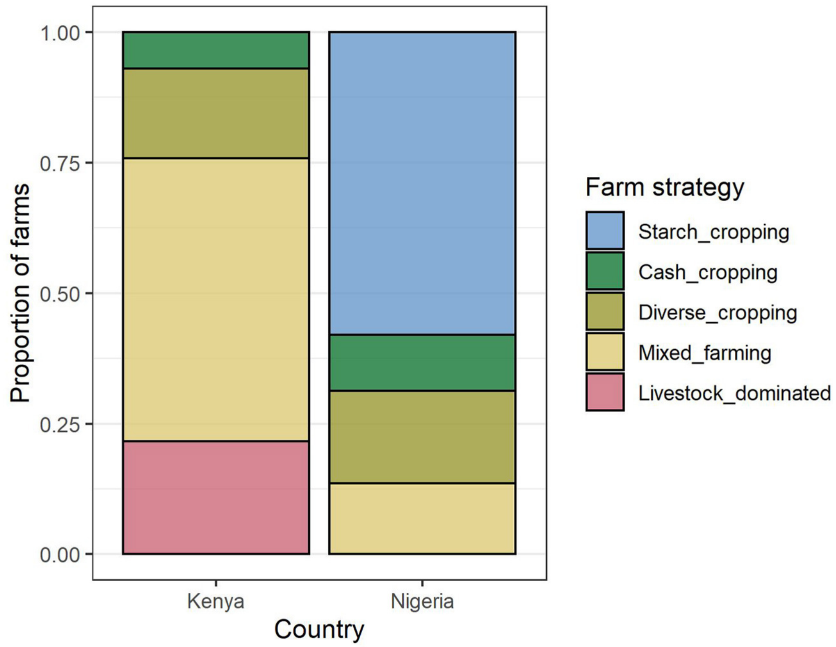

FIGURE 4 | Proportion of farms in each country belonging to each farm FC group, as identified by the hierarchical cluster analysis.

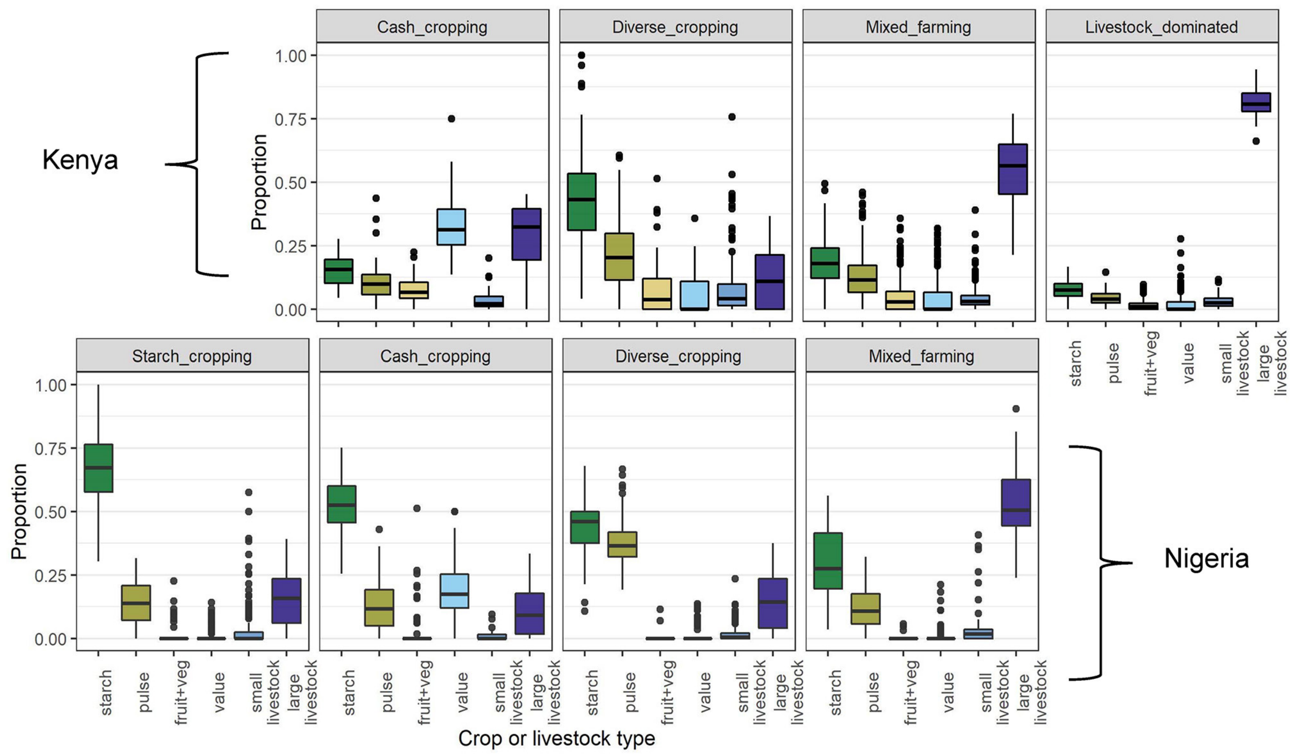

FIGURE 5 | Crop and livestock compositions of each FC group identified in the hierarchical cluster analysis. The y axis shows the weighted proportion of each crop and livestock type, the variables that were used in the cluster analysis, defined such that two TLUs are equivalent to one hectare of cropped land (see Section **Methods**). Thick bars indicate medians, boxes show interquartile ranges, whiskers show points up to 1.5 times the interquartile range (above and below the quartiles) and points indicate individual observations outside of this range.

TABLE 2 | The proportion of farms within each FC (rows) for each RE group (columns), in each country.

		Kenya			Nigeria		
FC	**RE**	**Low**	**Med**	**High**	**Low**	**Med**	**High**
Starch-dominated cropping					0.64	0.58	0.53
Cash cropping		0.03	0.08	0.09	0.07	0.14	0.11
Diverse cropping		0.18	0.18	0.15	0.17	0.14	0.21
Mixed farming		0.47	0.61	0.42	0.12	0.14	0.15
Livestock-dominated farming		0.32	0.13	0.34			

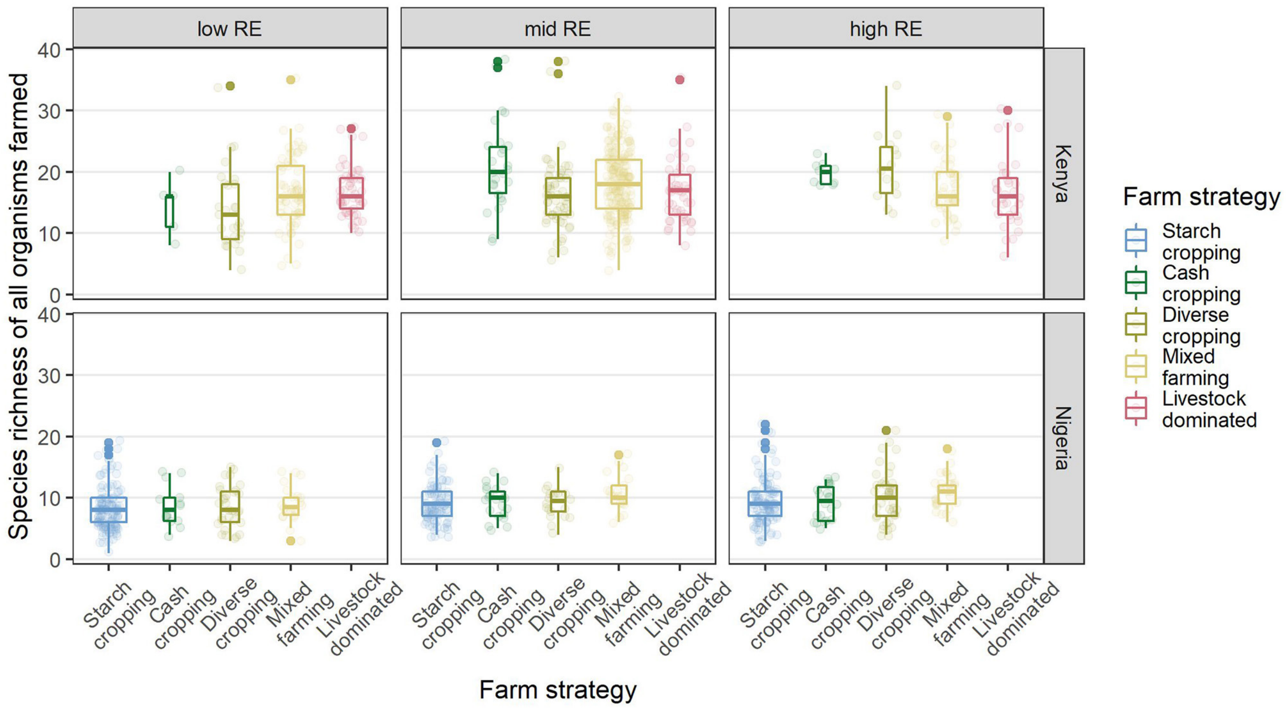

FIGURE 6 | Total farm species richness in different FC (x axis) and RE (panel columns) groups in Kenya and Nigeria (panel rows). Solid lines indicate medians, boxes indicate interquartile ranges, whiskers indicate points up to 1.5× the interquartile range while dots indicate outliers beyond that. Pale dots show the raw data (each point represents a farm).

richness was 6 and 4, respectively. Median livestock richness was 3 in Kenya and 2 in Nigeria.

Small differences in the mean farm species richness were observed between RE and FC groups in Kenya (**Table 3**), with typically higher diversity in the mid and high RE groups and in the cash-cropping and diverse cropping FC groups (**Table 4**). This pattern in Kenya was driven more by differences in fruit and vegetable species richness, and in crop richness, than by livestock richness (**Supplementary Figure S5**). In Nigeria, mean farm species richness only differed significantly among RE groups (**Table 3**), with the lowest richness in the low RE group. There was also substantial overlap in range among all groups in each country, indicating some equivalence in the opportunity space for system diversification across RE groups (**Figure 6**). In Kenya, the mixed farming and livestock dominated groups were, on average, more diverse than the cash cropping and diverse cropping groups in the low RE group, with the reverse pattern in the high RE group.

Food Security and Farm Income

The fitted models for each of the four food security and livelihood variables, modeled separately for the data for Kenya and Nigeria, are summarized in **Table 5** (for the reduced models) and **Supplementary Table S2** (for the full models). Model terms only involving RE and FC are concerned with how the mean response changes between the groups of farms defined by these characteristics, the combined (interaction) term indicating that the impact of FC on the mean response varied between the levels of RE (and vice versa). The main effect of SR indicates whether there was a consistent response to changes in this variable, with combined terms involving SR indicating that the effect of SR changes between the levels of RE or FC, or both, and the three-factor term indicating that the effect of SR changes in an inconsistent way across the combinations of RE and FC.

The four response variables in each country all have different forms of reduced models (**Table 5**). **Figures 7**, **8** show the fitted response patterns for each of the reduced models. In general, across both countries, higher RE was associated with lower food insecurity, more diverse diets, and higher incomes; however this relationship was modified by farm composition and farmed species richness, and their interactions. Farm composition tended not to have a strong overall effect, but did influence the effects of RE and SR for some response variables (**Table 5**), and in Kenya there appeared to be an association between FC and both dietary diversity and income, with cash cropping farms outperforming diverse cropping and mixed farming farms, and livestock dominated farms having the lowest values for these variables on average (**Figure 7**).

Increased species richness was associated with lower food insecurity (both FIES score and number of hungry months), higher dietary diversity and higher incomes within a given RE group. In Kenya (**Figure 7**), farms with a high species diversity in a low RE group could have better outcomes than those with a low species diversity in a high RE group. The main exception to this was for livestock dominated farms, where increased species richness was associated with a higher FIES score (higher insecurity) and lower dietary diversity—although the number of hungry months was still reduced, and incomes were higher. There were often too few datapoints within each RE group for cash cropping farms for the model fitting to give a clear idea of the effects of species richness in this farm composition type in Kenya.

In Nigeria (**Figure 8**), species richness had a consistently positive association with incomes, where again, on average, a low RE farm with high species diversity could outperform a high RE farm with low species diversity (**Figure 8D**). In contrast however, it appeared that higher SR was associated with increased food insecurity and reduced dietary diversity in most RE and FC groups, although the wider confidence intervals compared with Kenya suggest this conclusion should be drawn with caution. No association with species richness and the number of hungry months was observed in Nigeria.

A further analysis of the sources of dietary diversity (**Table 6**) showed that farmed species richness was associated with higher dietary diversity from on-farm food sources in both countries but had a stronger positive relationship with "other" food sources. In contrast, higher farmed species richness was associated with a decline in purchased dietary diversity. The estimated relationships between species richness and all three sources of dietary diversity are shown for each RE and FC group combination in **Figure 9**, to visualize the relative increases and decreases in each category that underpin the observed results for total HDDS in **Figures 7D**, **8D**.

No strong correlations between SR and variables used to create the RE clusters were found, indicating that these observed associations between outcomes and SR are not related to variability in resources within clusters. This indicates that our sampling approach (selecting randomly from lists of villages in each randomly selected ward, then including a small, medium, and large farm in each village to establish a gradient of RE) avoided structural bias that may have impacted the interpretation of the results. Most correlation coefficients were very low (between -0.2 and 0.2; **Supplementary Table S3**), demonstrating that no consistent patterns in RE variables could explain the observed effects of SR across all RE groups. However, somewhat larger correlations occurred between livestock holdings and SR in the low and mid RE groups in Nigeria ($R > 0.4$), so for these groups it could be questioned whether improved outcomes were in fact due to increased livestock holdings and not increased SR. In these groups, may be difficult to increase SR without also increasing livestock holdings, given the very low endowments observed for this group of <1 TLU per person and <1 ha cropland per person (**Table 1**).

TABLE 3 | Analysis of the impacts of the RE and FC classifications on SR in each country, with F-test statistics for Type III tests from ANOVA for marginal contributions respecting the marginality of model terms.

Country	Variable	*F*	df	*P*
Kenya	RE	2.359	2	0.095
	FC	1.790	3	0.148
	RE:FC	2.754	6	**0.012**
	Residual		554	
Nigeria	RE	3.158	2	**0.043**
	FC	0.351	3	0.788
	RE:FC	0.319	6	0.927
	Residual		522	

Bold type highlights significance at the 5% level.

TABLE 4 | Mean total farmed species richness (and standard errors in parentheses) of farms in each RE × FC combination in each country.

		Kenya			Nigeria		
FC	**RE**	**Low**	**Med**	**High**	**Low**	**Med**	**High**
Starch-dominated cropping					8.3 (0.3)	9.0 (0.4)	9.4 (0.3)
Cash cropping		15.0 (2.7)	21.3 (1.1)	19.7 (1.8)	8.6 (0.9)	9.3 (0.7)	9.2 (0.7)
Diverse cropping		14.1 (1.1)	16.1 (0.7)	21.0 (1.5)	8.6 (0.6)	9.2 (0.8)	10.2 (0.5)
Mixed farming		16.8 (0.67)	18.3 (0.4)	17.5 (0.9)	9.1 (0.7)	10.8 (0.7)	11.0 (0.6)
Livestock-dominated farming		16.9 (0.8)	16.7 (0.8)	16.6 (1.0)			

TABLE 5 | Model fitting results showing the fitted effects of RE and FC groups and species richness for the four livelihood outcome indicators, for the final reduced models.

		FIES score			Nr of months food insecure			Dietary diversity (bad season)			Farm income per person		
Country	**Variable**	x^2	**df**	***P***	x^2	**df**	***P***	x^2	**df**	***P***	***F***	**df**	***P***
Kenya	RE	3.061	2	0.217	8.181	2	**0.017**	5.523	2	0.063	18.830	2	0.088
	FC	5.829	3	0.120	3.107	3	0.375	14.125	3	**0.003**	35.180	3	**0.029**
	RE:FC	34.357	6	**<0.001**	13.931	6	**0.030**	18.612	6	**0.005**	41.720	6	**0.001**
	SR	0.165	1	0.685	0.032	1	0.858	0.134	1	0.714	57.100	1	**0.023**
	RE:SR	1.823	2	0.402	11.037	2	**0.004**	3.456	2	0.178	–	-	-
	FC:SR	5.023	3	0.170	7.803	3	**0.050**	12.877	3	**0.005**	–	-	-
	RE:FC:SR	29.820	6	**<0.001**	–	–	–	17.992	6	**0.006**	–	-	-
	Residual		542			548			542			553	
	AIC	3,718.699			2,172.533			2,566.809			2,385.479		
Nigeria	RE	22.431	2	**<0.001**	11.040	2	**0.004**	4.181	2	0.124	76.240	2	**<0.001**
	FC	1.634	3	0.652	6.377	3	0.095	1.044	3	0.791	–	-	-
	RE:FC	18.282	6	**0.006**	–	–	–	11.284	6	0.080	–	-	-
	SR	2.399	1	0.121	–	–	–	6.806	1	**0.009**	50.810	1	**<0.001**
	RE:SR	11.445	2	**0.003**	–	–	–	10.585	2	**0.005**	19.980	2	**0.007**
	FC:SR	4.919	3	0.178	–	–	–	1.333	3	0.721	–	-	-
	RE:FC:SR	28.462	6	**<0.001**	–	–	–	19.034	6	**0.004**	–	-	-
	Residual		509			527			509			527	
	AIC	2,679.444			1,430.554			2,628.334			1,893.955		

Chi-square test statistics are shown for analysis of deviance summaries based on GLMs assuming binomially-distributed data and a logit link function and F-test statistics for ANOVA based on linear regression assuming normally distributed errors. All test statistics are for Type III tests for marginal contributions respecting the marginality of model terms. AIC values are presented for comparison of these reduced models with the corresponding full models presented in ***Supplementary Table S1****. Variables marked with " – " were not included in the final, reduced model. Bold type highlights significance at the 5% level.*

DISCUSSION

Relationships Between RE, FC, and SR

The findings of our study indicate that although RE imposes a constraint on household food security and incomes, there may be potential for farmers to improve these outcomes through their choices of farm strategy, as characterized by FC and SR. The farmers in our study spanned a wide range of RE, from very small farms with substantially fewer productivity assets than one hectare and one TLU per person, as well as very low off-farm incomes, to farms with much larger areas of cultivated land and/or livestock herds per person, and much higher off-farm incomes (**Table 1**; **Supplementary Figure S1**). Low to intermediately resourced households tended to use higher rates of labor and fertilizer per cultivated hectare, a pattern also observed in western Kenya by Tittonell et al. (2005), suggesting more pressure to make the most of their available resources to achieve food security and adequate incomes.

There was little evidence in our study that RE influenced farm strategy choices in terms of either FC or SR. Similar proportions of farms in all RE groups were classified into each FC group (**Table 2**), and we observed greater within-group, rather than between-group, variation in SR across all combinations of RE and FC groups (**Figure 5**). This contrasts with other studies that found either that low RE limited farm capacity for species diversity (Wiggins et al., 2011; Snapp and Fisher, 2015; Kuivanen et al., 2016; Mellisse et al., 2018), or that higher RE facilitated specialization in fewer species (Kindt et al., 2004). We did find differences in FC groups and in both the mean and variance of SR between western Kenya and northern Nigeria. These differences were potentially a response to environmental constraints such as climate and the soil types on which crop and livestock species can be raised productively in a given region (Waha et al., 2018), although cultural preferences may also have played a role. However, within in each country, most FC groups were found in most regions (counties in Kenya and LGAs in Nigeria), and the distributions of SR values did not vary substantially between regions within country (**Supplementary Figure S6**). This suggests that even where local conditions influence which species are grown, farmers can substitute in locally adapted species (e.g., different types of "starch" or "value" crops) to fulfill their preferred farm strategy. Thus, our results suggest that opportunity exists across different levels of RE and different environmental conditions for farmers to intensify production through optimizing their crop and livestock choices.

Relationships Between RE, FC, SR, and Food Security and Livelihood Outcomes

Our results suggest that different combinations of RE, FC, and SR may result in different outcomes for food security and farm incomes (**Figures 7**, **8**). In general, farms from a higher RE group had better outcomes than farms from a lower RE group, in agreement with previous studies suggesting that higher RE entails not only a greater production base, but also a greater capacity to optimize the productivity of land and livestock held (Tittonell et al., 2005, 2010; Kuivanen et al., 2016). However, a key finding of our study is that increasing SR was associated

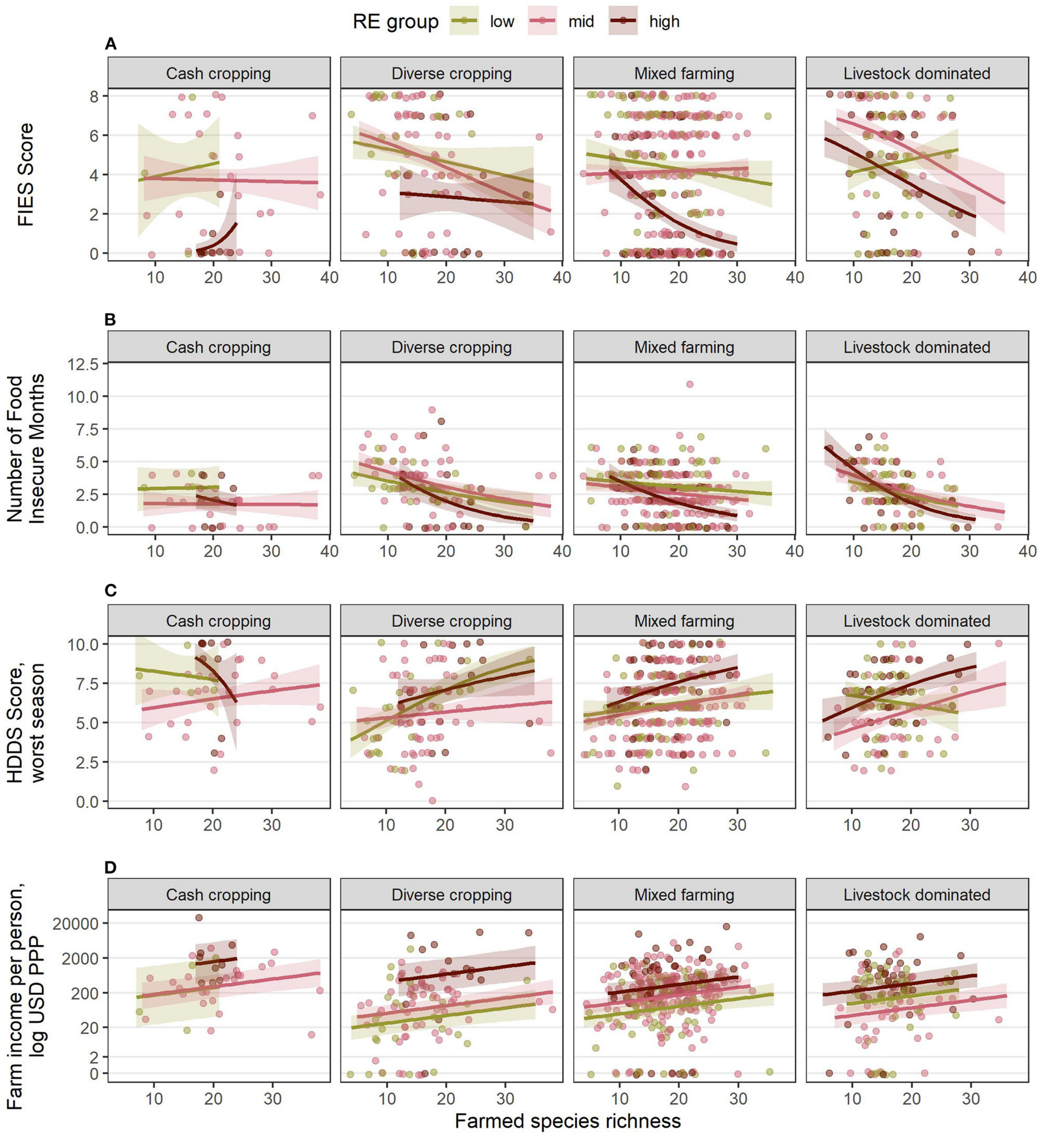

FIGURE 7 | Estimated relationships between livelihood outcomes in Kenya and the combinations of RE groups, FC groups and species richness (SR) derived from the final, reduced models for **(A)** FIES score, **(B)** number of food insecure months, **(C)** HDDS in the worst season, and **(D)** farm income per person, USD PPP. Lines indicate the estimated mean response, while shaded ribbons indicate 95% confidence intervals for the mean response. Graphs include extrapolation of the estimated relationships beyond the observed ranges of farmed species richness, to enable comparison of the shapes of the responses for different combinations of RE and FC groups, but extrapolated estimates should be interpreted with caution. Estimated responses for **(A–C)** are back-transformed from the logit scale on which the models were fitted. Estimated responses for **(D)** are shown on the log-transformed scale used for analysis (although axis labels show values on the linear scale). Points show individual (raw) datapoints from the survey responses, jittered around the true value so points do not obscure one another.

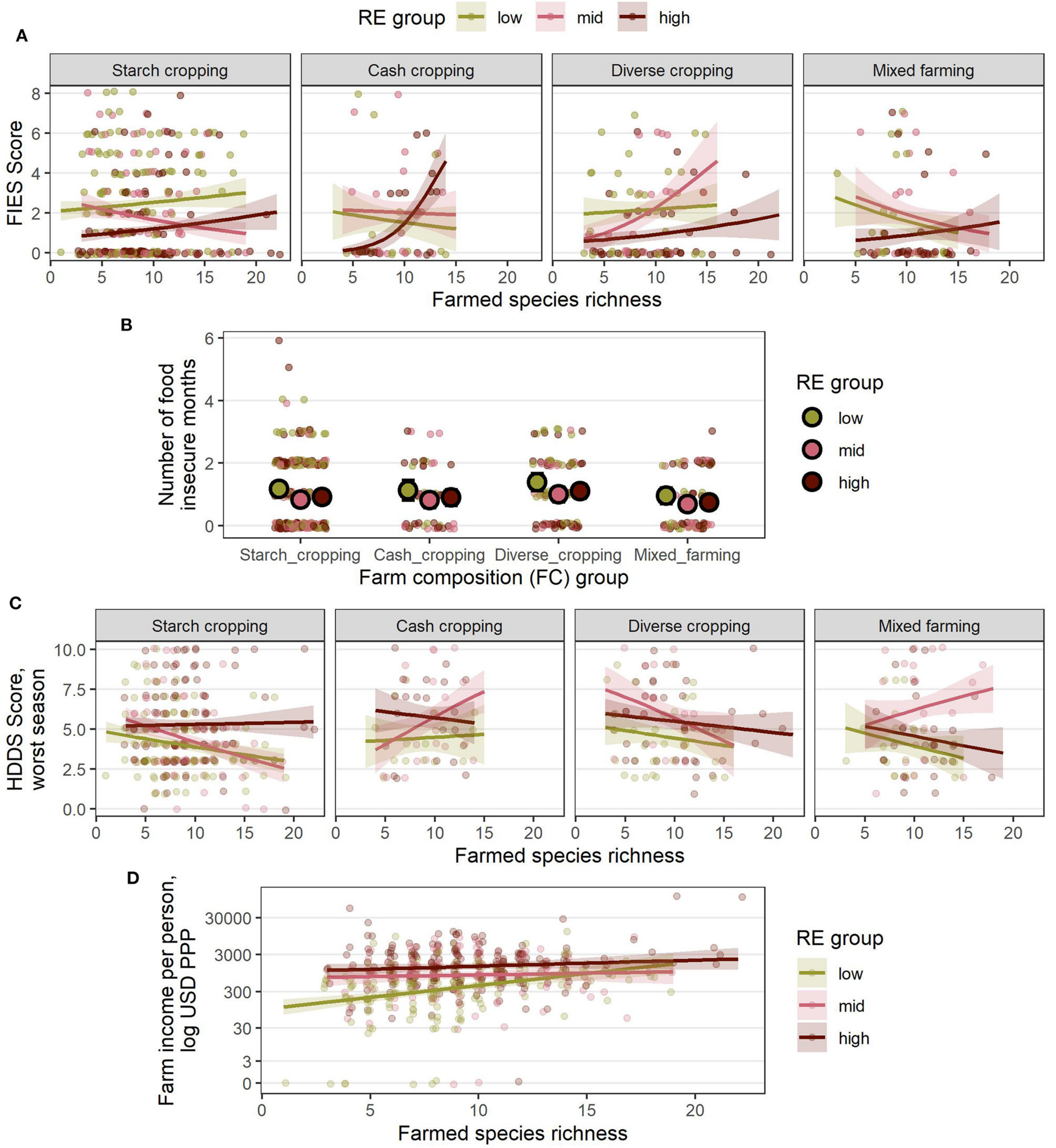

FIGURE 8 | Estimated relationships between livelihood outcomes in Nigeria and the combinations of RE groups, FC groups and species richness (SR) derived from the final, reduced models **(A)** FIES score, **(B)** number of food insecure months, **(C)** HDDS in the worst season, and **(D)** farm income per person, USD PPP. For **(A–D)**, lines indicate the estimated mean response, while shaded ribbons indicate 95% confidence intervals for the mean response. For **(B)**, large points indicate group means for each RE and FC combination and error bars indicate 95% confidence intervals (SR was not included in the reduced model of food insecure months in Nigeria). Graphs include extrapolation of the estimated relationships beyond the observed ranges of farmed species richness, to enable comparison of the shapes of the responses for different combinations of RE and FC groups, but extrapolated estimates should be interpreted with caution. Estimated responses for **(A–C)** are back-transformed from the logit scale on which the models were fitted. Estimated responses for **(D)** are shown on the log-transformed scale used for analysis (although axis labels show values on the linear scale). Points show individual (raw) datapoints from the survey responses jittered around the true value so points do not obscure one another.

TABLE 6 | Model fitting results showing the fitted effects of RE and FC groups and species richness for the three dietary diversity sources (purchased, farm-based and "other"), for the final reduced models.

		Farm-based			Purchased			Other		
Country	**Variable**	x^2	**df**	***P***	x^2	**df**	***P***	x^2	**df**	***P***
Kenya	RE	9.239	2	**0.010**	11.588	2	**0.003**	3.017	2	0.221
	FC	10.613	3	**0.014**	13.108	3	**0.004**	15.172	3	**0.002**
	RE:FC	17.128	6	**0.009**	–	–	–	16.802	6	**0.010**
	SR	6.619	1	**0.010**	15.147	1	**0.000**	5.379	1	**0.020**
	RE:SR	6.473	2	**0.039**	–	–	–	5.760	2	0.056
	FC:SR	7.681	3	0.053	12.116	3	**0.007**	13.874	3	**0.003**
	RE:FC:SR	–	–	–	–	–	–	18.160	6	**0.006**
	Residual		548			556			542	
	AIC	2,281.823			2,137.959			2,979.144		
Nigeria	RE	0.676	2	0.713	29.548	2	**<0.001**	8.597	2	**0.014**
	FC	3.611	3	0.307	16.818	3	**0.001**	–	–	–
	RE:FC	8.029	6	0.236	–	–	–	–	–	–
	SR	6.657	1	**0.010**	159.714	1	**<0.001**	88.811	1	**<0.001**
	RE:SR	5.091	2	0.078	–	–	–	–	–	–
	FC:SR	6.221	3	0.101	–	–	–	–	–	–
	RE:FC:SR	13.710	6	**0.033**	–	–	–	–	–	–
	Residual		509			526			529	
	AIC	1,619.813			2,311.231			1,729.564		

Chi-square test statistics are shown for analysis of deviance summaries based on GLMs assuming binomially-distributed data and a logit link function. All test statistics are for Type III tests for marginal contributions respecting the marginality of model terms. AIC values are presented for comparison of these reduced models with the corresponding full models presented in ***Supplementary Table S2****. Variables marked with " – " were not included in the final, reduced model. Bold type highlights significance at the 5% level.*

with improvements to most outcomes across all RE groups, and, critically, our results show that it is possible for farms with lower RE but higher SR to achieve similar levels of food security, dietary diversity, and incomes as farms with lower SR but higher RE. Although further research is required to confirm causality, our results indicate an important potential for farmed species diversity to contribute to improving food security and incomes for smallholder farms. In particular, SR had a consistent association with increased farm incomes across all RE and FC groups in both countries (**Figures 7D**, **8D**). In Kenya, high-SR low-RE farms also usually matched or outperformed low-SR high-RE farms for food security indicators across most FC groups (**Figure 7**).

FC group itself also influenced outcomes, although less consistently than changes in SR. In Kenya, the cash cropping and diverse cropping groups generally had a higher dietary diversity and farm income than the livestock-dominated group, and to some extent also the mixed farming group, for a given level of RE and SR. The effects of RE and SR were also often modified by the choice of FC group (indicated by significant interactions in **Table 5**): most notably, increasing SR in the low-RE livestock-dominated group in Kenya was associated with negative rather than positive outcomes, including a higher FIES score and a reduced dietary diversity score.

Positive effects of SR have been observed in many other studies. For example, crop diversity was found to be positively associated with on-farm-consumption of food crops as well as cash income from crops sold, in both northern Ghana (Bellon et al., 2020) and Uganda (Sekabira and Nalunga, 2020). Waha et al. (2018) found increased food security and food availability among households with a greater crop diversity across 18 African countries, and in western Kenya, Oduor et al. (2019) observed improvements to child nutrition as species diversity increased, while Boedecker et al. (2019) found that diversifying farm activities to include poultry-raising and homegardens improved dietary diversity. Alongside our results, these studies indicate that increasing farmed species diversity opens market opportunities for households, while also contributing to on-farm-consumption. This suggests that crop diversification could be more beneficial than specialization to smallholder farmers.

Other studies have suggested that the benefits of further diversification diminish above a certain level of diversity, and that other factors, such as market access, then become more important in generating further improvements to food security and livelihoods (Koppmair et al., 2017; Waha et al., 2018). In contrast, we observed continuing benefits across the observed range of SR for most of our outcomes in most combinations of RE and FC groups. We also observed smaller benefits of increased SR in northern Nigeria than in western Kenya, and farms in northern Nigeria typically had lower farmed species diversity than those in western Kenya—suggesting that already being at the higher end of the range of SR may have contributed to the stronger positive associations between SR and outcomes observed in western Kenya. These higher values of SR observed in western Kenya were largely driven by a greater number of fruit and vegetable species grown than in northern Nigeria (**Supplementary Figure S5**),

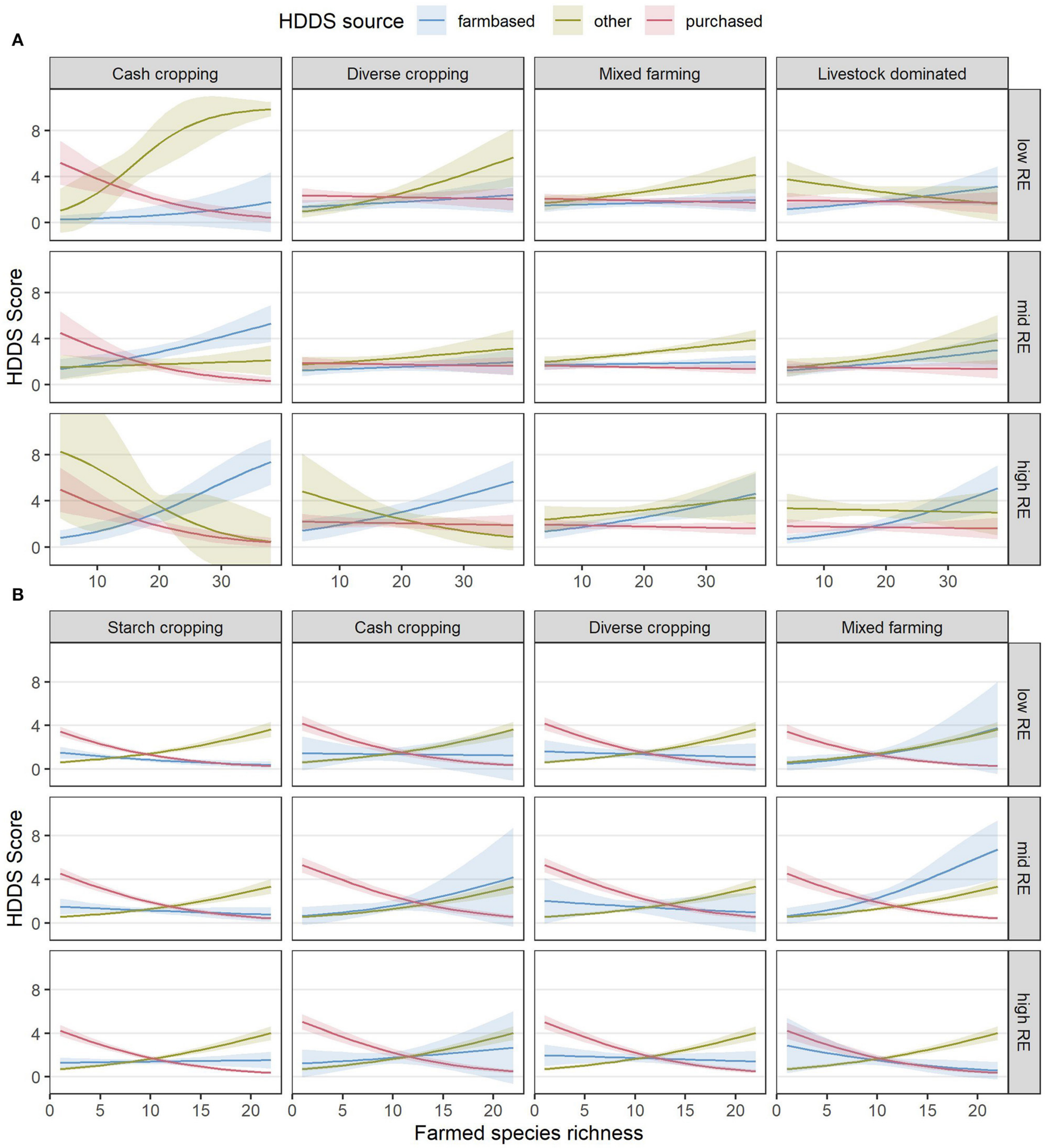

FIGURE 9 | Estimated relationships between diet diversity scores from different sources in Kenya **(A)** and Nigeria **(B)** and the combinations of RE groups, FC groups and species richness (SR) derived from the final, reduced models. Lines indicate the estimated mean response, while shaded ribbons indicate 95% confidence intervals for the mean response. Graphs include extrapolation of the estimated relationships beyond the observed ranges of farmed species richness, to enable comparison of the shapes of the responses for different combinations of RE and FC groups, but extrapolated estimates should be interpreted with caution. Estimates are back-transformed from the logit scale on which the models were fitted. Raw datapoints are not shown as there would be three per response (one for each source) leading to an uninterpretable plot; however the distribution of total HDDS can be seen in **Figures 6C**, **7C**.

suggesting that some benefits of increased SR may derive from the growing of diverse species in addition to the main crop and livestock activities, such as in diverse homegardens or integration of fruit trees in agroforestry layouts. This effect may not be captured by studies focusing only on crop and livestock diversity, rather than total farmed species richness, such as Waha et al. (2018). Kindt et al. (2004) and Degrande et al. (2006) both show that tree crops in particular can contribute to increased on-farm food consumption and incomes, while Boedecker et al. (2019) found that homegardens contributed positively to improved dietary diversity.

There were two important exceptions to the generally positive associations between increased SR and outcomes observed in our study. Firstly, increased SR was associated with increased food insecurity and reduced dietary diversity in livestock-dominated farms with low RE in Kenya, suggesting that it may be more beneficial for this group of farmers to focus on fewer species than to diversify. In general in Kenya, livestock-dominated farms, and to some extent mixed farms, tended to have poorer outcomes on average than diverse cropping and cash cropping farms (**Figure 7**). This observed negative effect of higher livestock holdings on outcomes, either directly or indirectly *via* modifying the effect of SR, is surprising given that many other studies indicate that higher livestock levels have a generally positive role in smallholder farms (Moll, 2005), including in western Kenya (Fuchs et al., 2019). Our result may reflect the "one-off" nature of our survey; perhaps it was undertaken during a period of relatively high crop product prices, favoring crop producers over livestock farmers, for example. The influence of current conditions on respondents' recall of food security and earnings is a known limitation of household surveys (Bell et al., 2016). Thus, we would urge caution in making strong inferences from the apparent negative effect of increasing livestock levels in our study, given its inconsistency with other literature.

The second case in which we observed SR to have a negative association with outcomes was with regard to HDDS across many RE and FC groups in Nigeria (**Figure 8C**). It is possible that dietary group richness is not directly related to farmed species richness, as multiple species belong to the same dietary group and so farmed species richness can be increased without then increasing the number of dietary groups. However, a closer investigation into the different sources of dietary diversity suggested a more complex relationship between SR and HDDS (**Figure 9**). Across both countries in our study, although more so in Nigeria, farm-based and "other" dietary diversity tended to increase with increased SR while purchased dietary diversity decreased. In Nigeria, the decrease in purchased dietary diversity outweighed increases in farm-based and "other" dietary diversity, resulting in an overall decline in HDDS as SR increased.

Previous studies have indicated that the relationship between farmed species diversity and dietary diversity varies with the importance of markets and the availability of wild foods (Ickowitz et al., 2019). In our study, "other" dietary diversity is predominantly made up of gathered, gifted, or exchanged foods, so the increase in "other" dietary diversity with increasing SR suggests that households with a higher SR may be embedded in more diverse neighborhoods where more food sources are available outside the formal economy. It is possible that such diverse, food-gathering and food-exchanging neighborhoods could exist as a result of poor market access motivating both an increase in SR for self-sufficiency and an increase in wild food gathering or informal food exchanges. Other studies have observed greater benefits of increased SR (Kissoly et al., 2020) as well as an increased reliance on forest resources (Degrande et al., 2006) when market access is lower. Despite the plausibility of this explanation, however, it seems unlikely to be the case in our study, given that both "other" dietary diversity and farm incomes per capita (a function of market access) increased with increasing SR, across all combinations of RE and FC groups in both countries. It remains unclear why farmers in Nigeria with a higher SR would purchase sufficiently fewer different food groups so that their overall dietary diversity drops below that of farmers with a low SR.

Implications and Future Research

Our study presents evidence that farms with high SR but low RE can achieve the same or better food security and income outcomes than farms with low SR and high RE, suggesting diversification could be a promising component of intensification for smallholders. These findings question the widespread perception that low-resourced smallholder farming systems are inherently inefficient and that Green Revolution technologies (i.e., crop breeding and accessible agrochemical inputs) are the best route toward improving both agricultural production and rural livelihoods (Pingali, 2012). Although accredited with widespread increases in calorie availability, the yield gains of the Green Revolution have been associated with the homogenization and up-scaling of farming systems, with increased costs to the environment (pollution, declining biodiversity and soil erosion) as well as threats to agriculture itself though declines in the nutritional value of staple crops (Fan et al., 2008; Gashu et al., 2021), the evolution of pesticide resistance (Hawkins et al., 2019), and declining soil health (Kopittke et al., 2019). In contrast, farming systems intensified *via* increasing crop and livestock richness, in combination with diverse homegardens and agroforestry, could mitigate these negative trends of homogenization whilst also offering substantial improvements to food security and nutrition.

However, further research is required to identify whether the relationship observed between SR and food security and incomes is truly causal, as other studies have found that increased SR may be as much a reflection of overall better farming capacity than a cause of increased productivity in its own right. For example, Mwololo et al. (2019) observed that crop diversity increases with access to agricultural extension services, so observed increases in food security and incomes may be due to an overall improvement in agronomic practices, while Nyberg et al. (2020) suggest that increased labor per hectare leads to higher crop diversity, and thus benefits may arise from this combination of increased labor intensity and increased crop diversity. Mechanisms by which increasing SR can improve food security and livelihood outcomes have been demonstrated, such as a higher SR increasing the diversity of foods available (Jones, 2017) and increasing productivity *via* nutrient complementarity and weed, pest and disease suppression (Isbell et al., 2017; Storkey et al., 2019). However, it is not certain that these mechanisms and anticipated benefits will occur in any given situation—for example, we note the negative impact of increased farmed species diversity on two outcomes for the low-RE livestock-dominated farms in western Kenya, and the negative relationship observed with purchased dietary diversity in northern Nigeria.

The substantial variation in outcomes observed in our study (**Figures 7**, **8**) indicates that additional variables must also moderate the relationship between SR and food security and incomes. Increasing SR may be just one of many farm practices that could improve food security and incomes within a given set of resource constraints. In addition, our investigation of dietary diversity sources suggests that the context around the farm—in terms of land-use and species diversity at the landscape or neighborhood level—may affect both the within-farm SR and the dietary diversity outcomes. Future research could address these knowledge gaps through taking a landscape-scale perspective of FC and SR, and/or through considering a wider range of explanatory variables, measuring factors such as access to markets, extension services, wild food resources, and community support networks, than we have in this survey.

The benefits of smallholder farm diversification must also be considered in a wider political and socioeconomic context, and our results here do not diminish the need for other actions to be taken to challenge food insecurity and poverty. Other authors have observed that although diverse farms can be much more productive, there is still a limit to the number of people that can be fed from a given land area (Conelly and Chaiken, 2000; Giller, 2020). Initiatives to improve land tenure and land availability, and to diversify rural economies, are therefore also important to increase food security, livelihoods, and wellbeing amongst rural communities.

Further insight into the roles of farm strategies in food security and livelihoods could be gained by performing similar analyses to those used in this study across a greater number and diversity of regions and countries across Africa and around the world. As noted previously, some differences in the observed effects of farm diversity between studies may relate to whether they consider just those plants and animals deemed to be "farmed crops and livestock" or whether they also include additional cultivated diversity such as fruits and vegetables in homegardens or as scattered trees. Here, our use of the RHoMIS platform can facilitate further research, given that other studies using the platform and contributing to the open database have collected data on crop, livestock and fruit and vegetable richness in the same way, as well as collecting the same indicators of resource endowment, food security and farm incomes. In our study, we did modify the data collected on areas cultivated under different crops in order to develop our FC classifications, so the FC groups would not be directly transferable to other RHoMIS datasets. However, we anticipate that key aspects of FC groups—for example the relative importance of livestock and of "value" crops—can be derived from the standard questionnaire. In addition, information is collected on whether farms have homegardens and practice agroforestry, and whether they use various synthetic and organic inputs and different soil and water conservation practices, so our typology of farms *via* RE and FC could be expanded to include other farm characteristics. The wider RHoMIS dataset therefore offers a rich resource to address many of the questions raised in this study about the role of different types of farmed species richness in improving food security and incomes, with regards to other agronomic practices and in the context of different levels of resource endowment.

DATA AVAILABILITY STATEMENT

An anonymised version of the raw data supporting the conclusions of this article will be made available by the authors, without undue reservation. Harmonised data from the core RHoMIS modules are also available within a larger open access RHoMIS dataset: RHoMIS (2021). "The Rural Household Multiple Indicator Survey (RHoMIS) data of 35,713 farm households in 32 countries", https://doi.org/10.7910/DVN/TFXQJN, Harvard Dataverse, V1, UNF:6:MuVv2zcmgeKv9w2G0072lA== [fileUNF].

AUTHOR CONTRIBUTIONS

All authors contributed to conceptualization and design of this study. AM designed the sampling framework with input from WW, KTA and CM, and WW and KTA led the surveys. CM completed the data analysis with input from AM and KTA. CM drafted the manuscript. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2022.744700/full#supplementary-material

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Which Innovative Cropping System for Which Farmer? Supporting Farmers' Choices Through Collective Activities

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Designing innovative cropping systems is an active field of agricultural research challenged by the agroecological transition. One of the challenges is to adapt cropping systems to the diversity of farms and contexts. For instance, in the cotton production zone of Burkina Faso differences between farm resources, agricultural situations and agronomic constraints have resulted in a wide range of farming systems. In this context, to break with the trend toward cotton production, we co-designed eight legume-based innovative cropping systems (ICS) likely to meet the objectives sought and the constraints faced by a wide range of local farmers, thus constituting a "basket of options". Our approach was to enable each farmer to choose the option they considered best suited to their conditions. To that end, the ICSs were implemented and discussed with farmers in participatory prototyping trials. After one season of co-evaluating the different ICSs, the farmers taking part in the co-evaluation were able to test an ICS on their own farm, by choosing and adapting one of the options. Thirty-nine farmers out of seventy-three chose an ICS to test. They were asked the reasons for their choice. Their selection criteria were analyzed in relation to comments made during collective activities organized in the participatory prototyping trials. To complete this analysis, we built an expert-based farming system typology and a statistical typology based on data collected in a rural household multi-indicator survey (RHoMIS) of 63 farms participating in this study. The two farming system typologies were compared, and the relationships between farming system types and the ICS tested on the farm were analyzed. We found that farmers did not really base their choice on their farming system. Rather, they used a wide range of criteria that varied from farmer to farmer, and they were influenced by what they had learned during the collective activities organized in the participatory prototyping trials.

Keywords: on-farm experiment, collective learning, participatory research, basket of options, farmers' criteria, farming system typology, legumes, West Africa

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INTRODUCTION

As defined by Altieri (2002), agroecology calls for the design of agricultural systems that (i) can be adapted to social and ecological uncertainties; (ii) are sustainable and resilient; and (iii) are based on the use of local resources and knowledge. It is therefore increasingly necessary to adapt techniques to local problems and to farmers' specific conditions. As each farmer is unique, with their specific means, knowledge, history, and socio-ecological context, there is no "silver bullet" (Meynard et al., 2012). The challenge is particularly acute in West Africa, where most farmers are smallholders with highly variable characteristics, particularly access to land, labor, equipment and knowledge, along with soil and climatic conditions, social rules, and access to cash flow (Tittonell and Giller, 2013).

In response, agronomists have gradually developed approaches that adapt technologies to the diverse needs of farmers based, for example, on farming system types (Landais, 1996; Touré et al., 2021). Farming system typologies provide simplified representations of farming system diversity, by grouping those that share the most uniform characteristics. The choice of characteristics on which the typology is built varies greatly from one typology to another, depending on its objectives (Alvarez et al., 2018; Tittonell et al., 2020). As typologies help in understanding and describing farm diversity, they can be used by development agents or researchers to target solutions for the problems encountered (Tittonell et al., 2010; Kuivanen et al., 2016), and to identify best-fit technologies (Giller et al., 2011). However, typologies involve a delicate trade-off between generic types that enable easy classification of farmers and require few exclusions, but make it difficult to find an option suiting all proponents of one type, and more precise types that exclude many specific cases (Descheemaeker et al., 2019).

Moreover, type-specific technical packages are often prescriptive and not flexible enough to be adopted by small-scale farmers (Tittonell and Giller, 2013; Ronner et al., 2017). An emerging way of overcoming this problem is to propose a variety of flexible technical options, sometimes called a "basket of options", from which each farmer can choose the system that best fits their own conditions (Descheemaeker et al., 2019; Ronner et al., 2021). This participatory research approach assumes that farmers are in the best position to know what is most suitable for their specific situation, and has the advantage of avoiding the need for agronomists to develop solutions adapted to each possible situation (Ronner et al., 2021).

This was the approach used in our study. In order to support farmers in the agroecological transition, several innovative cropping systems (ICSs) combining different legume species with a variety of local major crops were co-designed through on-farm innovation tracking carried out in the area, and participatory workshops organized in two communities. These various ICSs were then tested and collectively evaluated with a wide range of farmers in each community (Périnelle et al., 2021). After one season of co-evaluation of the different ICSs, each farmer was individually supported to test the option they found most interesting on their own farm.

As highlighted by Ronner et al. (2021), a knowledge gap remains on how to present the various technical options and how to support farmers in their selection of the options that are most relevant to them. The objective of this research was to propose and test an innovative approach to understand farmers' selection process and to help each farmer in selecting a relevant ICS to be tested and adapted on their own farm.

MATERIALS AND METHODS

Study Area

In this region of Burkina Faso, soil depletion and reduced productivity are issues increasingly being faced by farmers as it is often the case in West African cotton-production zones (Ripoche et al., 2015). This soil depletion is linked with a high land pressure (Jahel et al., 2017), a relatively low crop diversity (mainly maize-cotton rotation), and a limited access to fertilizers (Coulibaly et al., 2012).

The vast majority of farmers in the cotton production zone of Burkina Faso are smallholders. The farming systems there primarily produce cotton *(Gossypium hirsutum)*, but also cereals such as maize (*Zea mays*) and sorghum (*Sorghum bicolor*) (Coulibaly et al., 2012). Peanut (*Arachis hypogaea*) and cowpea (*Vigna unguiculata)* are the main legumes cropped, but on very limited areas and in very small quantities compared to other regions of Burkina Faso (Dabat et al., 2012). Cropping systems in the cotton production zone are based on short rotations (cotton-maize), animal traction, and the use of fertilizers and herbicides. The *Société Burkinabé des Fibres Textiles* (SOFITEX) influences the market and plays an important economic role in determining farmers' income. SOFITEX, which contracts with cotton farmers, supplies them with seeds and fertilizer for cotton and maize production through campaign credits repaid with the harvest (Andrieu et al., 2015).

Nomadic Fulani were traditionally the livestock herders in this area, but starting in the 1960s mixed crop-livestock systems using animal traction expanded into the cotton zone encouraged by SOFITEX, to facilitate tillage. Then, from the 1990s, crop farmers gradually invested in livestock (Andrieu et al., 2015), with draft cattle generally kept on the farm and fed with crop residues. Sometimes other livestock is kept by household members, or more often entrusted to Fulani herders, who are now mostly sedentary, but for them livestock raising is now mostly a marginal activity. Many crop farmers who have become wealthy from cotton production are able to invest in livestock to reduce the risks associated with soil degradation and to diversify their activity (Andrieu et al., 2015). Fulani herders raise cattle and grow cereals, mainly for household consumption, using the residues as cattle fodder. They rarely grow cotton and do not use mineral fertilizers, as the organic manure produced by their livestock is largely sufficient to fertilize their staple crops (Vall et al., 2017).

According to several studies conducted in the cotton production zone of Burkina Faso (Vall et al., 2006, 2017; Andrieu et al., 2015), farming systems diversity can be captured through the degree of livestock and cropping activities, respectively reflected in the number of cattle and the cultivated area. They divide farmers into three main types: crop farmers, crop-livestock farmers and livestock farmers. Even though farm structures have evolved since the establishment of these typologies, they are still used by researchers and advisors in the area, by adapting threshold values between types, as these two components (crop and livestock) remain the most discriminant variables of local farming systems.

Following our previous study (Périnelle et al., 2021), two communities in two different municipalities in Tuy Province

TABLE 1 | Description of the 8 ICSs proposed to farmers as implemented in the PPT after soil preparation by animal traction (ridges spaced 70 cm apart) and application of glyphosate to the whole plot.

ICSs	Sowing description	Chemical inputs	Main harvested products	Type of ICS
1. Sorghum-peanut intercropping	Sorghum and peanut planted with a dibble on the same day, alternating in the same row; sorghum density (80 × 70 cm) higher than the peanut density (40 × 70 cm)	None	Sorghum: grains Peanut: grains	Intercropping
2. Sorghum-soybean intercropping	Soybean planted with a dibble 10 days before sorghum in the same row; soybean density (80 × 70 cm) higher than sorghum density	None	Sorghum: grains Soybean: grains	Intercropping
3. Red cowpea in intra-annual succession with white cowpea	Red cowpea sown early (30 × 70 cm density); white cowpea (30 × 70 cm) sown after red cowpea harvest	Insecticide on cowpea	Red cowpea: grains White cowpea: grains or leaves	Intra-annual succession
4. Red cowpea in intra-annual succession with maize	Red cowpea sown early (30 × 70 cm density); maize (40 × 70 cm) sown after red cowpea harvest	Insecticide on cowpea	Red cowpea: grains Maize: stalks as fodder	Intra-annual succession
5. Sole Mucuna, in rotation with cotton or maize	Mucuna sown with a dibble at 60-cm intervals on the ridges (60 × 70 cm density)	None	Mucuna: biomass as fodder	Fodder
6. Mucuna in relay with maize	Maize sown first at normal density (40 × 70 cm); Mucuna (80 × 70 cm) sown between maize rows after maize ridging	NPK on maize	Mucuna: biomass Maize: grains	Fodder
7. Sole pigeon pea, in rotation with cotton or maize	Pigeon pea sown with a dibble on the ridges (40 × 70 cm density)	None	Pigeon pea: biomass or grains	Fodder
8. Maize-pigeon pea intercropping	Maize sown first at normal density (40 × 70 cm); pigeon pea (40 × 70 cm), sown between maize rows 3–4 weeks after maize sowing	NPK on maize	Pigeon pea: biomass Maize: grains	Fodder

were selected for further participatory activities: Boni and Founzan, both in Tuy province. These communities were selected mainly because literature detailing their farming systems was already available, and connections with community leaders and farmers had already been established (Coulibaly et al., 2012). Both communities are part of the same agroecosystem in the cotton production zone. However, Boni is located close to the cotton processing plant, so cotton is very important for farmers, while Founzan is located close to a dam, so farmers produce a wider range of products, including fish and irrigated vegetables.

Implementing Participatory Prototyping Trials in Each Community

In the two selected communities, various innovative cropping systems were set up in participatory prototyping trials (PPTs) in 2017, integrating different legume species and different types of integration (rotation, relay, intercropping, intra-annual succession) with sorghum, maize, or cotton. The range of ICSs was chosen to respond to a range of different functions, and to meet the expectations of the main types of farmers in the area (crop, crop-livestock, and livestock farmers). In order to ensure that the systems met farmers' criteria, they were co-designed based on: (i) on-farm innovation tracking conducted throughout Tuy province (systems 1, 2, 3,4, 5, and 7, **Table 1**) (Périnelle et al., 2021), or (ii) farmers' criteria expressed during participatory workshops organized prior to implementing PPTs in each village (systems 6 and 8, **Table 1**). All the implemented ICSs were new to the participating farmers.

One PPT was set up in each community, both managed by the research team, comprising one researcher and one technician. The PPTs were set up to allow farmers to observe and compare the various cropping systems and to be used as a support for debate and co-evaluation with farmers. The layout of the PPTs was the same at the two locations and was organized to display a variety of cropping systems, without randomized replications, but organized to facilitate comparisons. Each PPT was divided into 18 plots (each covering 400 m^2) containing either an ICS, or peanut, cowpea, soybean, sorghum, maize, or cotton monocultures. Fertilizers were applied at typical rates for the region (150 kg/ha of NPK 14-23-14 and 50 kg/ha of urea 46% on cotton and maize, none on the other crops). The land was prepared by plowing and ridging with animal traction in compliance with local practices.

During "field days", farmers were invited to collectively discuss and evaluate each PPT plot. In each community, a contact person (in both cases a literate farmer from the community known by the research team) was tasked with inviting between 20 and 30 farmers representing the different local types of farmers (crop farmers, livestock farmers and mixed crop-livestock farmers) of different ages and gender. After the first field day, a few additional farmers joined the group after having heard of it from other participants. In all, 73 farmers took part in at least one field day. Two field days were organized on the

PPT in each community. The first field day was held in August 2017, 3–4 weeks after sowing, and was used to present the trial: each plot was described and the farmers asked questions, but did not evaluate the ICSs. The second field day was held in September 2017, just before harvest, and was used to ascertain the farmers' evaluation of the ICSs. Both field days started with an explanation of the reason for holding the day. Then, each ICS was examined plot by plot. On the second field day, to obtain the farmers' evaluations, the researcher asked the farmers what they liked or disliked about the ICS they saw before them, and what they would do to improve it. The questions were purposely open to avoid influencing the farmers' responses, and the farmers were encouraged to react to each other's comments. The farmers' discussions were recorded and minutes were taken. The recording and the minutes were subsequently discussed between the researcher and the technician and compiled. The compilation was used to describe the criteria used by the farmers to assess the ICSs during the field days.

A Basket of Eight Options

Eight ICSs were proposed to the farmers (**Table 1**): (i) sorghum-peanut intercropping; (ii) sorghum-soybean intercropping; (iii) red cowpea (*Vigna unguiculata)* in intra-annual succession with white cowpea; (iv) red cowpea in intra-annual succession with maize; (v) Sole Mucuna (*Mucuna pruriens)*; (vi) Mucuna relayed with maize; (vii) sole pigeon pea (*Cajanus Cajan);* (viii) maize-pigeon pea intercropping (**Table 1**). ICSs showing similarities (species involved and organization of the species mixture, use made of production) were grouped in the same "type of ICS" (**Table 1**, column "type of ICS") to facilitate statistical comparisons between them.

Organization and Monitoring of Farmer Adaptation Trials

After harvesting the PPT, the farmers were given the opportunity to choose one ICS to test on their farm in "farmer adaptation trial". The trials, which were conducted in 2018, were individual 0.25 ha plots, set up and managed by each farmer in parallel with their usual systems.

The seeds were provided free of charge, to make it easier to compare "farmer adaptation trial" and to be sure that seed availability would not be an obstacle to the implementation of the trial as some species were not common in the region. The quantities distributed were calculated on the basis of the seeding rates used in the PPTs, but the farmers were not obliged to reproduce the PPT rates and were free to adapt the management of the ICS. For the same reasons, fertilizer (NPK) was distributed for the maize sown with the pigeon pea or the Mucuna at the same rates as those used in the PPTs (i.e., 150 kg/ha of NPK 14-23-14). For the other crops, no fertilizer was distributed because none was used in the PPTs; however, the farmers were free to add fertilizer. No other chemicals were distributed.

In August 2018, seeds for the trial were given to each individual farmer. During the distribution, an open-ended questionnaire was submitted to each farmer to understand their choice of ICS. The main question was "Why did you choose this ICS?" Then, more questions were asked to better understand the reasons for their choice.

TABLE 2 | Variables extracted from RHoMIS data.

Name of the variable	Type of data	Description
AE	Quantitative (number)	Adult equivalent (1 for the 1st adult + 0.5 for the others > 11 years old + 0.3 for < 11 years old)
land_cultivated	Quantitative (ha)	Number of hectares cultivated in 2017
AE_per_Land_Cult	Quantitative (ratio)	Number of adult equivalents according to the cultivated area
cattle	Quantitative (number)	Number of cattle owned by the household
TLU	Quantitative (number)	Tropical Livestock Unit (1 for an adult bovine, 0.4 for a calf; 0.2 for an adult sheep or goat, etc.)
TLU_per_Land_Cult	Quantitative (number/ha)	Ratio of the number of tropical livestock units to the number of hectares under cultivation
land_coton_prop	Qualitative ordinal (between 0 and 4)	Proportion of cotton crop among all the farm annual crops (0: no cotton, 5: only cotton)
land_maize_prop	Qualitative ordinal (between 0 and 4)	Proportion of cotton crop among all the farm annual crops (0: no maize, 5: only cotton)

The farmers' selection criteria were analyzed based on their responses recorded in the semi-structured interviews. Our final interpretation of farmers' choice criteria was based on (i) the reasons for choosing an ICS given by the farmers during individual open-ended interviews, and (ii) the consistency between those reasons and their first collective assessment of a given ICS in the PPT during the field days.

The following cropping season, the farmers were able to choose an ICS again to test on their farm. They had the option of continuing the same ICS ("carry on with the same ICS"), choosing another ICS from the seven proposed options (the maize-pigeon intercropping was no longer proposed because no one chose it in 2018) ("change ICS"), or to stop doing a trial ("stop trial"). Farmers were individually asked their choice and the reason of their choice about 2 months before sowing the second trial.

Farming System Typology Used to Analyze Farmers' Choices

Farming system typologies were built on information collected through RHoMIS-type guided surveys created by the International Livestock Research Institute (ILRI). This type of survey targets rural households (one survey per household, or farm), and is designed to rapidly characterize a set of standard indicators including farm functioning, agricultural production, and wealth level (Hammond et al., 2017). RHoMIS surveys consist of core modules and additional optional modules. The survey was adapted to the present study by adapting the vocabulary used in the mandatory module, especially units of measure.

In the field, surveys were conducted by two trained interviewers, one in each village. Surveys were conducted with 63 of the 73 farmers who had taken part in the activities, including 37 of the 39 farmers who conducted a "farmer adaptation trial". Of the 10 farmers missing, six could not be reached and four were excluded from the final analysis due to data inconsistency. All the farmers answering the questionnaire gave oral consent for the use of their data. Sixteen variables were extracted from these surveys to be compared with the farmers' choices (**Table 2**). The variables corresponded to the standard variables used to build farming system typologies (Berre et al., 2019).

A functional expert-based typology of farming systems was built on the criteria proposed by Vall et al. (2006). The authors classed farms in the cotton production zone of Burkina Faso according to three main types: crop farmers, crop-livestock farmers and livestock farmers, which were broken down into several sub-types. The typology proposed by Vall et al. (2006) used structural features of farming systems to reflect their functioning, especially in terms of crop and livestock system interactions, which is still relevant (Vall et al., 2017). We could therefore adapt the functional typology to the context of our study by updating the threshold numbers for cattle and cultivated areas. This "functional typology" used the number of cattle owned by the household ("cattle" variable) and the number of hectares cultivated ("land cultivated" variable) to class farmers in various types The updated threshold values were part of the results of the analysis and are explained in the results section (see section Links Between Farmers' Choices and Their Farming System Types).

A statistical typology was also built using seven variables from RHoMIS data: number of adult equivalent (AE), cultivated area (land_cultivated), number of adult equivalents according to the cultivated area (AE_per_Land_Cult); number of Tropical Livestock Unit (TLU); number of Tropical Livestock Unit according to the cultivated area (TLU_per_Land_Cult); proportion of cotton crop (land_cotton_prop); proportion of maize crop (land_maize_prop). The multivariate analysis chosen to build this statistical typology is a classic two-step method. First, a principal component analysis (PCA) was implemented on the discriminant variables to synthetize the diversity of the sample into two principal components of the PCA (data- or dimension-reduction process). In a second step, a hierarchical clustering (HC) analysis was carried out on these synthetic principal components. Both the PCA and the HC were

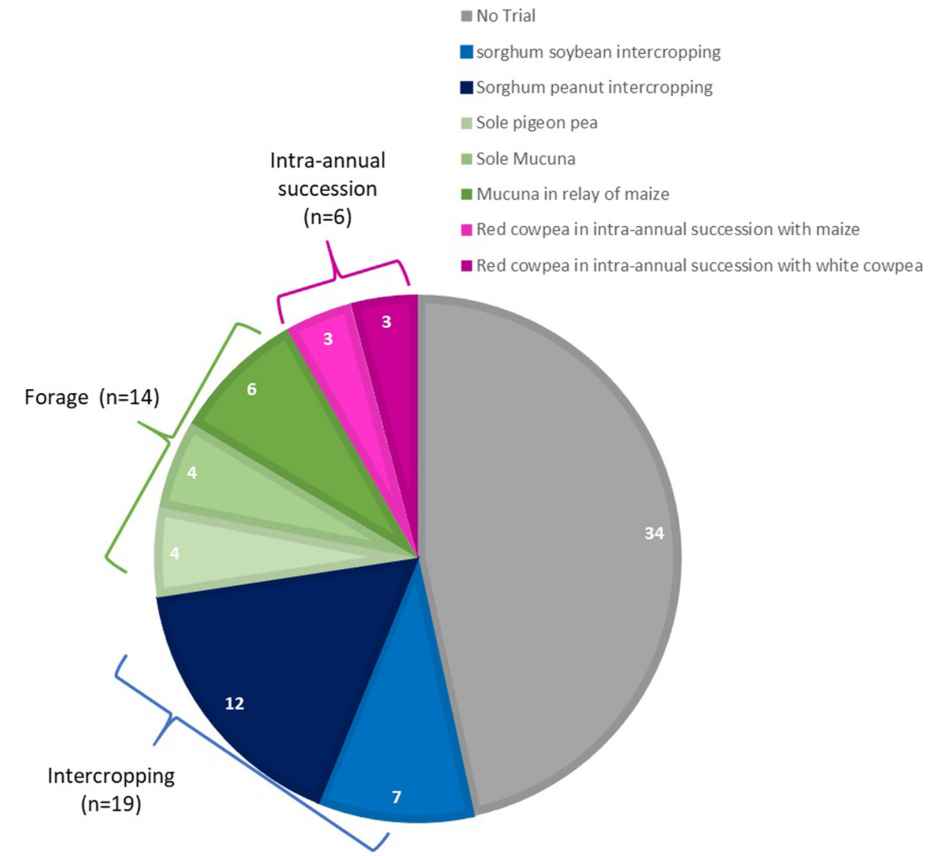

FIGURE 1 | Distribution of the 73 farmers who took part in the field days, according to the choice of ICS implemented in the Farmer Adaptation Trials. The number farmers for each type of ICS (intra-annual successions in purple, fodder crops in green, sorghum-legume intercropping in blue) are indicated in brackets.

implemented under (R Core Team, 2021) using the ade4 package (Thioulouse et al., 2018).

RESULTS

The ICSs Selected by the Farmers

Of the 73 farmers who had taken part in at least one field day, 39 (53%) conducted a "farmer adaptation trial" (**Figure 1**). Intra-annual successions were less frequently selected (six farmers) than fodder (14 farmers) and intercropping (19 farmers). The sorghum-peanut intercropping system was by far the most frequently selected ICS (12 farmers). In the fodder type, no farmer selected maize-pigeon pea intercropping. The main reason given by the farmers was fear of competition between pigeon pea and maize. Mucuna as a relay crop with maize was less of a problem, as Mucuna was sown in the maize row, after the maize had been ridged.

Farmers' Selection Criteria

For the ICSs implemented by the farmers, **Table 3** details the criteria that they used to select their ICS.

The criteria used to select the ICSs were classed in six categories (**Table 3**): 1. Production/yield; 2. Soil fertility; 3. Flexibility/Risk management; 4. Post-production strategy; 5. Labor management; 6. Learning and knowledge. Criterion types 1, 2, 3, 4, and 5 were the types of criteria used by the farmers during the field days (Périnelle et al., 2021). The new type of criterion, "learning and knowledge", was related to the farmer's level of knowledge about the ICS, which they may have acquired through personal experience, or during the field days in the PPTs. The choice of an ICS may have been motivated by the fact that the farmer was used to grow the crop species making up the ICS, particularly in the case of associations and intra-annual successions. Conversely, some farmers wanted to test something very new, like Mucuna (fodder).

Differences were observed between the evaluation criteria used during the field days and the criteria used for the implementation of the ICSs (highlighted in the gray boxes in **Table 3**). Some differences were due to the nature of the criteria: an evaluation criterion may have been assessed positively or negatively by the farmers, whereas all the selection criteria given by the farmers referred to positive aspects of the selected ICS, if only in comparison with the other options. For instance, during the field days, intercropping systems were evaluated negatively in terms of work management, whereas the farmers who selected them said they were easier to manage than intra-annual successions (type 5 criterion): they consider that intra-annual succession requires twice as much work as sole crop, while intercropping would require an intermediate workload. The selection criteria appeared to be more diversified than the evaluation criteria used during the field days. For instance, some farmers selected an ICS because there was no need for fertilizer (type 3 criterion), whereas it was not mentioned during the field days.

The intercropping systems were the only ICSs chosen for all 6 types of criteria, including for criterion 5 "Labor Management", which was not cited for the intra-annual successions, and by only one farmer for fodder (pigeon pea). Three farmers chose sorghum-peanut intercropping, with "labor management" as their main selection criterion. They considered that sorghum was not very susceptible to weeds, that ridging was possible and that intercropping required less work than intra-annual successions. These three farmers explained that seeing the intercropping systems in the participatory prototyping trials compared with monocrops motivated them (criteria 6): they noticed that sorghum intercropped with peanuts was better developed (taller, greener) than sorghum alone.

Several farmers said they chose their ICS based on the plot they planned to test: they first chose the plot, then chose the ICS that would work best on that plot, taking soil type and location into account.

Intra-annual successions were selected based on all criteria, except "Labor Management," as the farmers considered that growing two crops doubled the amount of work. Moreover, most of the farmers agreed on the importance of tilling, or at least of scraping the soil between the two crops. Intra-annual successions were mainly chosen because two harvests were possible with a fairly low risk, since the biomass of the second crop could be used, and because the first crop was harvested early, and consequently helped in the lean season.

The selection criteria for the fodder crops were more varied than for the others, hence the separate presentation of the three options in **Table 3**. However, trends appeared for all three fodder options. The choice of the type of fodder was mainly based on the criterion (i) "Post production strategy," as it was easy to produce good quality fodder (except for one farmer who chose pigeon pea to produce peas for family consumption), and (ii) "learning and knowledge"; Mucuna and pigeon pea are not very common in the region, and the farmers who chose to test them were curious to see how they fared in their plots. The "Soil fertility" criterion was cited by only one farmer, for whom fodder production was not the priority, and who therefore did not mention the "Post production strategy" criterion. This farmer chose Mucuna as a replacement for maize, even though he owned only one ox, as he wanted to plant a new crop that could help restore his soil fertility, while growing maize for family consumption. One farmer who had already tested pigeon pea for fodder decided to test it again because he understood that it is a biennial species that can be mowed 2 years running ("Labor Management" criterion).

One criterion was mentioned only by women: less fertilizer and animal traction required ("Flexibility/ Risk management" criterion) compared to the other options. These women did not have access to farm resources. One woman chose intercropping over intra-annual succession because she was concerned that she would not have access to oxen for plowing early enough for the succession, and the other chose red cowpea in intra-annual succession with white cowpea, mainly because red cowpea is harvested earlier than other food crops, and can consequently help in the lean season.

A comparison of the selection criteria for the three types of ICS showed that each type had specific advantages for the farmers who chose them. According to the farmers, the different types of ICSs allowed them to solve different problems: fodder production for cattle (fodder), or productivity per ha (intercropping and

TABLE 3 | For each type of ICS implemented by the farmers (in the columns), the selection criteria they declared in response to the open-ended question "Why did you choose this cropping system?" are presented according to the corresponding type of criteria (in the rows).

ICS / Type of criteria	Intercropping (19 farmers)	Intra-annual successions (six farmers)	Fodder		
			Sole Mucuna (four farmers)	Sole Cajanus Cajan (four farmers)	Mucuna in relay with maize (six farmers)
1. Production/ yield	*Productivity per ha* *"I will make better use of my area by growing two crops on the same plot."*	2 crops per season *"I hope to harvest maize, but if not, I will at least have the stalks for fodder"* *"I will harvest twice"*			
2. Soil fertility	Beneficial effect of legume on sorghum "Peanut looks good for sorghum "Peanut helps sorghum "	Beneficial effect of the legume on the soil "Cowpea is good for the soil" " To enrich the soil "	Beneficial effect of the legume on the soil *"I heard it's good for the soil, so I want to see for myself"*		Beneficial effect of the legume on the soil *"Mucuna is good for the soil"*
	Beneficial effect of the legume on the soil "It's good for the soil" The association will help me restore my soil" "Soy is good for the soil" ICS adapted to the plot *"I took the system that would work best on the plot I chose for the trial"* *"Because it will fit in well with the type of soil in the plot I just cleared."* *"Because I am going to put it on a poor soil where there is striga."* *"It is the only system that fits in with the plot I have chosen for the trial."* *"This is the only system I could put on the accessible plot I have available."*				
3. Flexibility/ Risk management	Less restrictive than other ICS *"It's not too limiting: I don't need to add fertilizer, and I can't do the succession because I don't have an ox to plow when I want."*	Multi-use of the second crop *"Even if I do not harvest the grain of the second crop, I will have fodder."* *"The white cowpea leaves can be used to feed the family (soup) or the animals."*			
		Less restrictive than other ICS *"I won't need to buy fertilizer."*			
4. Post production strategy	Contributes to the family's diet *"We harvest two crops, one of which is peanuts, which can be eaten fresh from the field."* *"I will harvest two crops."* *"To benefit from two crops"* *"The crop can be eaten by the family."* *"In addition, we can eat the peanuts fresh from the field."*	Help in the lean season *"Red cowpea is early, it will help in the lean season"* *"Red cowpeas will help in the lean season."*	Good quality fodder *"To produce fodder for my cattle."* *"I know it is a very good fodder, it will be for my 6 oxen"* *"I want fodder for my oxen that I use to plow".*	Good quality fodder *"To produce fodder"* *"I wanted to make fodder, I will try Mucuna at the next opportunity≫*	Good quality fodder *"To get the forage and the corn stalks for the animal. " "To get fodder for my 10 cattle"* *"Maize is the main food for the household and I will also have fodder" "To have fodder for my 5 oxen in addition to maize for the family"*

(Continued)

TABLE 3 | Continued

ICS Type of criteria	**Intercropping (19 farmers)**	**Intra-annual successions (six farmers)**	**Fodder**		
			Sole Mucuna (four farmers)	**Sole Cajanus Cajan (four farmers)**	**Mucuna in relay with maize (six farmers)**
	Possibility of using the stalks for animals *“The stalks of both crops (sorghum and peanuts) can be used for animals.* *“And in addition, we have the stalks for the animals.”*	Second crop with good forage value *“I will have maize stalks that are still green for the animals”*		Helping to feed the family *“Rather to produce peas for the family’s food”*	
	Possibility of selling the products *“We will process and sell the soybeans”*				
5. Labor management	Less labor intensive than other ICS *“The work is easy: we can weed with animal traction (ridging and weeding).”* *“Sorghum is quite resistant to weeds.”* *“This system requires less work than the successions.”* *“This system does not require too much work compared to the others.*			Possibility to let it grow back for 2 seasons *“We sow it once and we can mow it and it grows back for 2 years*	
6. Learning and knowledge	Known crops *“I already know sorghum and peanuts”* *“I’ve done soybeans before”* *“I did the same type of intercropping last year≫*	Known crops “I am used to growing cowpeas” “I know cowpea well.”	Already tested *“I’ve already tried it and found it to be very good fodder.”*	Already tested *“I’ve done it before and I liked it but I lost the seeds.”*	Already tested *“I’ve done Mucuna before.”*
	Motive from visiting the PPTs *“The PPTs made me want to try it.”* *“This is what I liked best during the field days.”* *“During the visits, I saw that peanut helps sorghum.”*		Wants to test a new system “I’ve never grown crops just for animal feed, I want to test it.”	Wants to test a new system *“Out of curiosity: I don’t know anything about it, so I want to test it.”*	Wants to test a new system *“I wanted something new but not too new, and I’ve done Mucuna alone before.”*

Some criteria were mentioned by various farmers, and some farmers mentioned several criteria, so have several quotes. The shaded boxes correspond to criteria that differed from the evaluation criteria formulated during the field days.

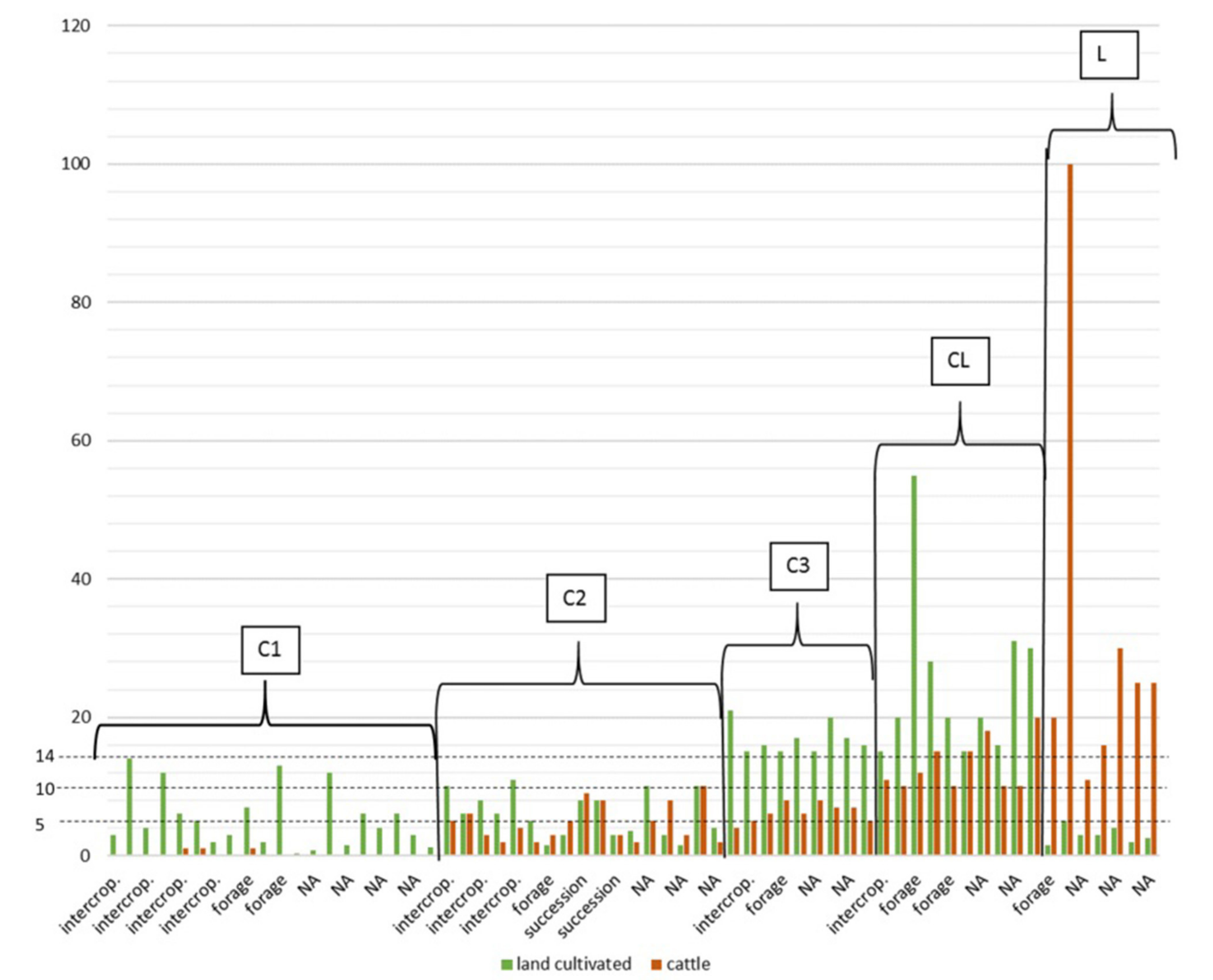

FIGURE 2 | Distribution of the farming system types according to the number of ha cultivated (in green) and the number of cattle (in brown) on the *y*-axis, and the type of ICS tested in their farmer adaptation trials, or the choice not to take part in the farmer adaptation trials (NA), on the *x*-axis. The threshold values for cultivated area ($\leq$ 5ha for livestock farmers, $<$ or $\geq$ 14 for crop and crop-livestock farmers) and number of cattle ($<$10 for crop and crop-livestock farmers or $\geq$10 for livestock farmers) are shown on the *y*-axis.

intra-annual succession). In addition, the farmers pointed out that the different types of ICS were suited to different levels of soil fertility: Mucuna and pigeon pea as the sole crop being suitable for poor soils, sorghum-legume intercropping for moderately fertile soils, and Mucuna relayed with maize for richer soils.

Links Between Farmers' Choices and Their Farming System Types

According to the RHoMIS data, the cultivated area and the number of cattle owned varied widely between farms (**Figure 2**). However, it was possible to define thresholds for these two farming system characteristics that discriminated relatively uniform types and sub-types of farming systems (**Figure 2**; **Table 4**). There was no significant difference in the distribution of the sub-types between Boni and Founzan (Chi2 test) (**Table 4**).

The "crop farmers" type refers to farmers with fewer than 10 head of cattle, among which we differentiated those who had fewer than two (C1) (**Table 4**). Consequently, farmers classed as C1 did not have the two oxen required for animal traction, and consequently faced strong constraints for plowing and ridging as they depended on the availability of oxen belonging to other farmers and could not plow when they wanted. None had more than 14 ha of cultivated land. C2 farmers also had <14 ha of cultivated land but owned enough cattle for animal traction, so it was easier for them to plow and ridge their field for weed management. C3 farmers had more than 14 ha of cultivated land, but like the other crop farmers they owned fewer than 10 cattle.

TABLE 4 | Description of the types and sub-types of farmers based on the functional typology proposed by Vall et al. (2006) (no AT: no animal traction), and farmers' choice of ICS according to their type of farming systems.

Types		**Crop farmers**			**Crop-livestock farmers**	**Livestock farmers**
Sub-types		**C1**	**C2**	**C3**	**CL**	**L**
Land cultivated (ha)		≤14	≤14	>14	>14	≤5
Cattle (number of heads)		≤1 (no AT)	2 ≤ X < 10	2 ≤ X < 10	≥10	≥10
Number of farmers in Boni		10	7	4	3	3
Number of farmers in Founzan		10	10	5	7	4
TOTAL number of farmers		20	17	9	10	7
Farmers' choice (number of farmers)	No trial	8	5	4	5	5
	Intercropping	8	5	2	2	
	Fodder	3	2	3	3	2
	Intra-annual succession	1	5			

Farmers' choice are in boxes colored according to the choice: no trial in grey, sorghum-legume intercropping in blue, fodder crops in green, intra-annual successions in purple.

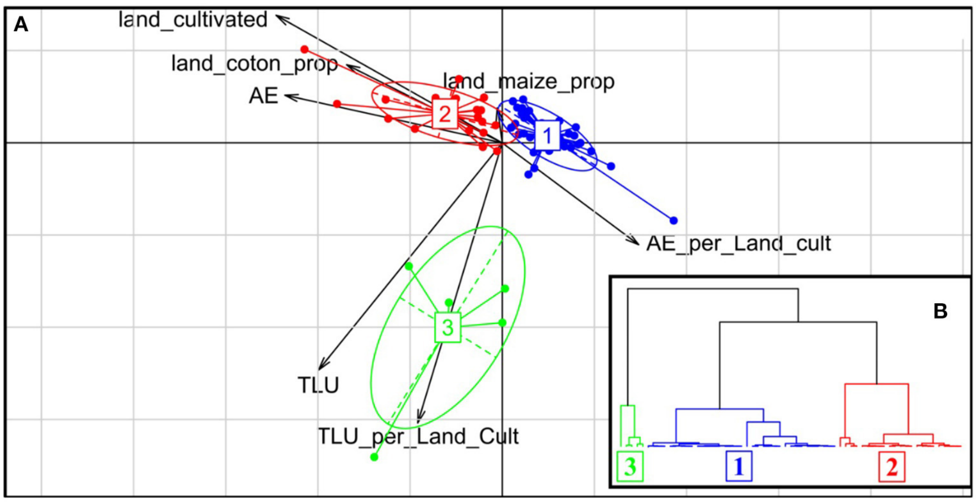

FIGURE 3 | Graphical exploration of the Principal Component Analysis (PCA) and Hierarchical Clustering (HC) for 63 farms: **(A)** Projection of variables (arrows) and of farmers (colored points) according to their types on the PC1–PC2 plane, **(B)** Cluster dendogram.

Farmers who owned more than 10 cattle were either "Crop-Livestock farmers" (those who cultivated > 14 ha (type CL), or "Livestock farmers" [those who cultivated < 5 ha (type L)]. This number of cattle implied that, when they took care of the cattle themselves, a significant share of farm resources (especially labor, crop residues) was used for the cattle, but they had access to manure for their field. For all the crop-livestock farmers, owning animals meant a diversification of their production and therefore a distribution of risks. The livestock herders, who were Fulani herders, had specialized their production into cattle production and had very small cultivated land areas, all used for household consumption.

Table 4 also shows the number of farmers who made each choice (no trial, intercropping, fodder, and succession) according to their expert-based farming system type. There was no statistical difference in the distribution of choices for each farming system type at the 0.05 threshold (p-value = 0.233 with Fisher's exact test). However, a larger proportion of farmers who did not conduct a trial was observed among the farmers who owned the most livestock: half the crop-livestock farmers and over 70% of the livestock farmers did not conduct a farmer adaptation trial. Type A2 farmers were the most likely to conduct a trial. In addition, intra-annual successions were only found among small-scale farmers (A1 and A2), and more often among those who owned at least two head of cattle (A2), hence who had access to animal traction. Three farmers who declared they owned no cattle (A1) chose a fodder crop: among them, one farmer chose Mucuna relayed with maize and two chose pigeon pea, whose seeds could be consumed by the household. The distribution of choices by farmers with more than 14 ha was roughly the same, whether they owned fewer than 10 cattle (A3) or more than 10 (EA), with a major interest in fodder systems.

The multivariate analysis of the nine chosen variables clearly revealed three statistical farming system types (**Figure 3**). Type 1, called "subsistence-oriented" grouped small farms with a limited cultivated area (average of 5.6 ha), and limited livestock (average

TABLE 5 | Main characteristics of farming system types and type of SCI choices according to the statistical typology.

		Type 1 Subsistence-oriented	Type 2 Cotton-based	Type 3 Livestock owners
Farm characteristics (type average value)	land_coton_prop	1	2.4	1.2
	land_maize_prop	2.1	2	2.2
	AE	3.9	7.6	5.4
	land_cultivated (ha)	5.6	18.3	3.3
	AE_per_Land_cult	1.8	0.7	2.2
	TLU_per_Land_Cult	0.4	0.5	8.8
	TLU	1.7	8	29.6
Comparison with functional typology (**Table 4**)	C1	**18**	2	
	C2	**13**	4	
	C3	2	**7**	
	CL		**10**	
	L	2		**5**
Total number of farmers		**35**	**23**	**5**
Farmers' choice (number of farmers)	No trial	13	10	4
	Intercropping	12	5	
	Fodder	7	5	1
	Intra-annual succession	3	3	

The variables used as farm characteristics are detailed in ***Table 2****.*
Bold values in shaded boxes are matches between the functional typology and the statistical typology.
Farmers' choice are in boxes colored according to the choice: no trial in grey, sorghum-legume intercropping in blue, fodder crops in green, intra-annual successions in purple.

of 1.7 TLU) (**Figure 3**; **Table 5**). Type 2, called "cotton based", had a much larger cultivated area (average of 18.3 ha) and type 3, called "livestock owners" had a much larger number of livestock units (average 29.6) (**Figure 3**; **Table 5**).

The statistical typology overlaps fairly well with the expert-based typology: most of the C1 and C2 farming systems belong to type 1, the C3 and CL farming systems belong mostly to type 2, and the L systems correspond more to type 3 (**Table 5**). In the same way as for the expert typology, a chi-square test did not reveal any significant effect of the farming system type (according to the statistical typology) on the choice of implementing a trial, or not, or on the choice of ICS (**Table 5**).

Farmers' Evaluation of Their ICS Choice

The following cropping season, out of the 39 farmers having tested an ICS in 2018, 23 continued the same type of ICS in 2019, because they were satisfied enough after having conducted the first trial. Of the 16 farmers who decided to change their type of ICS, six declared to be satisfied with the type of ICS chosen but wanted to try another type (**Figure 4**).

DISCUSSION

A Wide Range of Farmers Involved

In this study, we used a participatory action research approach (Faure et al., 2010), seeking to help farmers belonging to a wide variety of farms to change their practices (introducing more legumes in their cropping systems). From a development point of view, we "targeted" and involved as many participants or "beneficiaries" as possible, while remaining able, from a research perspective, to monitor each one for a comprehensive analysis of the process. According to Phillips et al. (2014), who studied farmers' field schools, there are three ways to target farmers for action: (i) open targeting, i.e., open to all farmers, (ii) targeting through a selection process, with established criteria that beneficiaries must meet, or (iii) targeting an identified group, for example farmers belonging to a specific farming system type, as is often the case in development projects. Rather than targeting specific categories of farmers, we chose open targeting, where all activities were open to all interested farmers.

In each community, heterogeneous groups including farmers with different means of production, farmers for whom the main activity was livestock, and women who generally had very limited access to means of production, were called upon. Such a variety of participants was a source of enrichment for the process through the exchanges that took place between the different participants both during and beyond the field day. For instance, a crop farmer who tested a fodder type of ICS may have been influenced by livestock farmers during the collective activities. In general, the discussions that took place during the collective activities in the PPTs were richer when they took place between farmers with different types of farming systems. As shown by Dolinska and d'Aquino (2016), heterogeneous peer networks are conducive to innovation.

Even though all farming system types were targeted, there was still selection based on farmers' motivation and interests in taking part, and arising from the method used to invite them (via the contact person's network). As a result, some farmers did not participate in the process: this was particularly true of farmers who were marginalized, including women and minorities. For instance, relatively few Fulani herders took part in the activities. This may have been because they were less interested in cropping legumes (small cultivated areas, access to organic manure), or because they were often left out of the community. Also, six

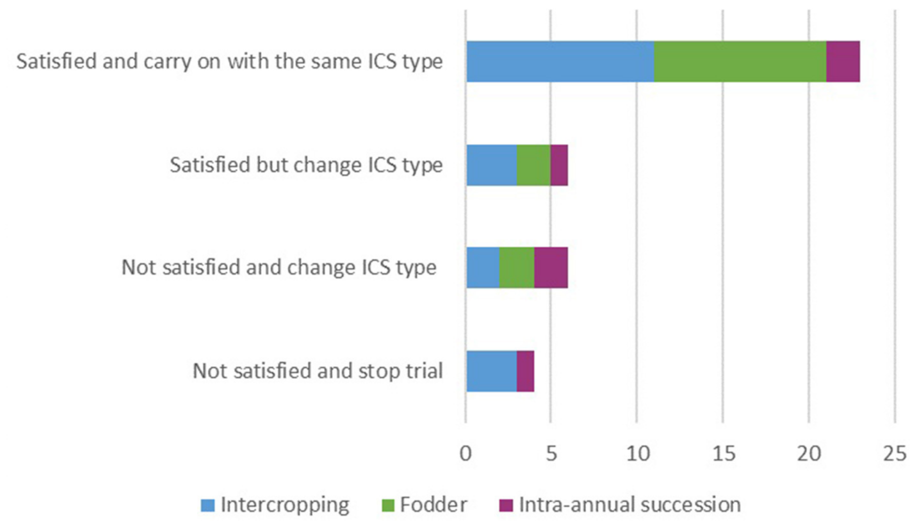

FIGURE 4 | Distribution of the type of ICS tested in 2018 based on the evaluation of the ICS made by each farmer.

of the nine women who took part in the collective activities did not have access to a plot to conduct a farmer adaptation trial, and found themselves excluded from the activity. Phillips et al. (2014) pointed out that the poorest or most marginalized individuals, particularly women, are often excluded from rural development activities, except when they are specifically targeted and when activities are tailored to suit them. Even women with equivalent access to productive assets as men are more likely to be excluded than men, one reason being that they do not belong to the same network as their male counterparts (Ragasa et al., 2013). However, with the appropriate support, being part of group working on agricultural innovation may be an opportunity to get less marginalized (Classen et al., 2008). In our case, to be more inclusive, it would have been necessary to work on the obstacles that limited the participation of vulnerable farmers, for example by facilitating their access to the necessary resources (land, animal traction, labor), which was not in the scope of this study.

The sample of farmers in this study was not strictly representative of the general population of farmers in the area, but all types of farmers were represented (Périnelle et al., 2021). In participatory research, researchers often choose the stakeholders they work with in order to ensure a certain representativeness of the study area, with the objective of being able to extrapolate their results to situations with similar characteristics (Faure et al., 2010). This was not the choice made in this study, as farmer motivation was the main condition for their participation. In our approach, it was the co-design process that could be extrapolated, rather than the ICSs.

A Variety of Selection Criteria Matured in the PPTs

We noted both convergences and divergences between the farmers' selection criteria for the choice of ICS and evaluation criteria expressed by farmers during the field days. The five criteria used for evaluation during the field days were also mentioned in their choice, and, half of the time, mentioned for the same reasons during field days and for the choice of ICS. On the other hand, some criteria were evaluated differently. For example, during the field days the amount of work was seen as a difficulty involved in intercropping, whereas in the choice leading to the farmer adaptation trials, several farmers asserted that intercropping required less work than intra-annual successions. Moreover, a new evaluation criterion emerged between the field days and the choice of an ICS that was related to the learning process during the collective activities in the PPTs. The collective activities gave the farmers the opportunity to mature their evaluation, by observing the cropping systems, and through exchanges between peers and with agronomists (Cooreman et al., 2018).

Indeed, during the collective activities in the PPTs, the farmers acquired a clearer picture of the relative advantages of each system and enriched their knowledge of the ecosystem services provided by legumes, such as soil fertility improvement or household food diversification (Kerr et al., 2007). Thus, even though farmers did not directly manage and work in the PPTs, several collective evaluation activities allowed them to acquire actionable knowledge on the various options. The acquisition of this knowledge was key, as they may not have chosen the option that best responded to their problem if they had not acquired enough knowledge to make an informed choice (Sumberg et al., 2003), which required a consistent and regular involvement of the farmers in the participatory process (Misiko, 2013). Moreover, thanks to collective debate around several systems, the farmers did not focus on a single technical solution. For instance, some farmers chose to try another ICS the second year, although they were satisfied with the system they chose the first year. While peer-to-peer exchanges are known to have an impact on farmers' perceptions, with learning related to diverse perspectives (Chantre et al., 2015; Cooreman et al., 2018), the exchanges and the learning process enabled by them are difficult to accurately track and evaluate, especially regarding their direct effect in changing practices (Aare et al., 2020).

Some of the farmers chose an ICS based on the knowledge they already had of it; either because they were familiar with the crop species involved, or because they were curious to try something new. In the first case, the farmers tried a new cropping system without requiring a lot of new knowledge and saw it as less risky. This choice may constitute an "antecedent" in the farmer's trajectory and allow a progressive change that can lead to a successful trajectory of change (Lamine, 2011). In the second case, the farmers chose ICSs that were very new to them, and therefore quite risky. In this case, exchanges between farmers helped to demystify the theoretically less known ICSs. While highly participatory approaches are sometimes criticized for promoting the status quo, for various reasons such as farmers' risk aversion (Abadi Ghadim, 1999), in our case the dynamics initiated during the field days helped the farmers to enter a trajectory of change, and may allow continuity of the trajectory beyond the support period (Mawois et al., 2019).

Links Between Farming System Types and Farmers' Choice of ICS

Links between farming system types and the farmers' choices (to conduct a trial or not, and which ICS to choose) were analyzed through two distinct farming system typologies, both RHoMIS survey data: (i) a functional expert-based typology built from a typology established in the same area and recently used (Andrieu et al., 2015; Vall et al., 2017), and (ii) a statistical typology built from classic farm characteristics used to build typologies (Berre et al., 2019). As highlighted by Berre et al. (2019), expert-based and statistical typologies are complementary for understanding farm diversity: expert-based approaches are more explanatory, whereas statistical typologies generally aim to extract types from a large number of data in a process that is intended to be more reproducible and less subjective than expert-based typologies. In our case, the two typologies built were consistent with each other, but no systematic links between farmers' choices and farming system types were found.

Our results showed that farmers with different farming system types may choose the same ICS for different reasons. The different legume species used in the ICSs can provide multiple services (Vanlauwe et al., 2019; Reckling et al., 2020). For instance, pigeon pea has a great carry-over effect on maize, and may be chosen by crop farmers for that, it can be mowed for fodder and be of interest to livestock farmers, or harvested at maturity for the grains, which then contribute to the diversification of the household diet. Mucuna can be grown on very poor soils, where it will help restore fertility, which is a crop farmer's criterion, and is a good quality fodder for livestock farmers.

The lack of a clear link between farmers' choices and the selected RHoMIS variables may be partially due to the fact that these data were based on self-reported interviews, which is a source of uncertainty, and to the limited number of farmers (37 having set up a trial). The number of farmers was restricted to enable the follow-up of each case, but usually RHoMIS surveys are used on larger samples, which makes the data more robust (Fraval et al., 2019). In our study, the use of RHoMIS surveys allowed us to obtain homogeneous indicators on heterogeneous farmers that were suited to our study's objectives. In addition, in the case of women and young people, who are not farm managers and only have the power to decide over their own plot (Gafsi, 2007), analyzing the links between the farming system characteristics and their choices has been probably disrupted by the fact that they made decisions based on their own access to farm resources (plot, labor, animal traction), rather than on their family farming system.

Studies on links between farmer choices and preferences and their farming system characteristics give highly variable results. For the choice of whether or not to conduct a trial, Sumberg et al. (2003) found no clear link between a farmer's socio-economic characteristics and their inclination to conduct a trial, which is consistent with our results. However, many studies show a link between farmers' preference of practices and their farming systems or socio-economic characteristics. For instance, Khatri-Chhetri et al. (2017) found links between farmers' preferences on Climate Smart Agriculture technologies, that are discussed with farmers but not implemented, and socio-economic characteristics; and Zongo et al. (2016) found links between cropping systems implemented by farmers and the farm's level of endowment in Burkina Faso. One difference between those two studies and ours is that there was no medium of exchange (the PPTs in our case) between agronomists and farmers that enabled the different types of actors to share observations and knowledge on innovative systems (Trompette and Vinck, 2009; Klerkx et al., 2010). Our results suggest that collective activities helped the farmers to mature their choice of ICS through collective learning. This learning occurred by seeing, comparing and debating the ICSs, but also by exchanging information with peers and with agronomists. For example, some farmers learned about the existence of a potential market for certain legumes during the collective activities, which influenced their choice, thinking beyond the limits of their farms.

A Co-designed Basket of Options to Meet Each Farmer's Specificities

A basket of options will only be relevant and effective if the options are sufficiently diverse and adapted to the variety of farmers involved (Ronner et al., 2021). We proposed a variety of eight ICSs with the objective of meeting the expectations of the different farmers in the community, and addressing the complexity of their conditions (Descheemaeker et al., 2019). As in the "option by context approach" we considered that the suitability of agronomic innovations depends on many factors (bioclimatic conditions, access to a market and value chain, farming practices, household characteristics, advisory services, etc.) that vary on a fine scale (Sinclair and Coe, 2019), and even from farmer to farmer. In order to increase ICS diversity, we diversified in particular (i) the production objectives to which the systems could respond (e.g., production of forage for cattle for "fodder" crops, productivity per ha for "intercropping" and "intra-annual successions"), (ii) the degree of novelty of the innovations with new species such as Mucuna and pigeon pea, or known species such as cowpea and peanut, and (iii) the design method of the ICS (inspired by on-farm innovation tracking or designed *de novo*). However, increasing the number of options may increase the proportion of them uninteresting for farmers (Ronner et al., 2021), as was the case of the pigeon pea/maize intercropping system that did not interest any farmer.

Beyond the relevancy of the options, the ability of the farmers to select the right one is crucial. To make a relevant choice, it is important that farmers acquire enough knowledge on the options through their participation. Many approaches other than ours use a central field trial as a medium for experimentation and information flow between agronomists and farmers, such as Farmer Field Schools used as an advisory tool (Duveskog et al., 2011), or mother and baby trials used for participatory varietal selection (Snapp, in Bellon and Reeves, 2002). In both cases, the level of farmer participation in trial design and implementation can vary from consultative to collaborative. Yet, Bakker et al. (2021), who studied the case of farmer field schools, showed that involving farmers in decision-making contributes to enabling a transformative learning process. In our approach, the farmers were involved from the beginning of the ICS co-design process: each ICS was discussed upstream during the participatory workshops and then, during the field days, the farmers actively took part in assessing the options by asking questions, debating between themselves and proposing ways of improvement. Throughout the process, the agronomists took into account suggestions made by the farmers. By involving the farmers from the beginning of the process and by establishing a relationship based on mutual trust, we fostered a transformative learning process (Reed, 2008).

Rather than deciding on the best practices to be implemented, farmers were supported in finding their own solutions, so that the solutions were as relevant as possible to their particular situation, even if they were not optimal from an "agronomist-expert's" point of view (Catalogna et al., 2018). Some farmers' criteria might not seem relevant to agronomists, for instance if they are not directly related to solving the farmer's problem (e.g., making the same choice as his neighbor, choosing a cropping system to obtain expensive seeds for free). However, as farmers have detailed knowledge of their local environment, situations, priorities, and evaluation criteria, they are better placed than an outsider to find innovative solutions that suit them, even if the latter has a detailed and appropriate knowledge of the biological and ecological processes in play (Sumberg et al., 2003). We also considered that there are different valid solutions for each problem and that a farmer may find some solutions more useful than others depending on their priorities, knowledge, means, and history (Darnhofer et al., 2010). In our approach, the agronomist no longer prescribes solutions, but supports the farmers in building their solutions. This change of posture belongs to a change of paradigm where farmers are involved in the design work and provided with design support tools (Salembier et al., 2018). This way of actively involving farmers can help to address the complexity of the issues related to the agroecological transition (Klerkx et al., 2010), but needs substantial institutional innovations in order to be scaled up (Nelson et al., 2019).

CONCLUSION

Our approach, consisting in setting up participatory prototyping trials and organizing collective activities, was relevant for helping farmers to make the best choice of an adapted innovative cropping system from a basket of options. Interactive learning, enabled by collective activities, helped each farmer to make an informed choice. By presenting a variety of ICSs, it was possible to work with a variety of farmers, with contrasting interests in potential alternative agricultural practices. Farmers' criteria and choices depend on many complex factors, including social norms, means of production, agronomic conditions, but also their personality, preferences, and skills, and these cannot all be diagnosed by agronomists. However, farmers can be supported in making their choices through collective activities and participatory trials.

Our approach, should now be applied to produce knowledge on participatory approaches, and for development purposes. In addition to furthering the participatory co-design process initiated in our study, it would be interesting to support farmers in adapting the management of the selected cropping system to their own conditions via a step-by-step design process, thus putting farmers in a position to design their own systems through an empowerment process.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors upon request.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

AP did the field work (implementation of the various activities, data collection, and analysis) and was the main writer of the article. DB contributed to the data analysis and the realization of the figures. ES and J-MM supervised the whole study and contributed to the writing of the article. All authors contributed to the article and approved the submitted version.

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Market access and dietary diversity: A spatially explicit multi-level analysis in Southern and Western Kenya

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The risk of malnutrition, particularly micronutrient deficiency, is high in large parts of Sub-Saharan Africa for smallholder farmers. Access to diverse and nutritious food is a key component of food security, and a major development objective. It is widely accepted that good access to markets can play a key role in improving nutrition at the foodshed level. However, the magnitude and even the direction of the effect of increased market access on household dietary diversity (and thus food security) is not universal, with studies showing divergent results. One reason for these divergences may be that models do not account for place-based mediation effects, that is, farmers' local context can affect whether (and the extent to which) access to market is important to their nutrition. Drawing on household survey data from 914 Kenyan smallholder farmers from ten counties in South and West Kenya, we used a novel methodology to evaluate the role of market access in determining household dietary diversity. This methodology combines the clustering of households along places with similar characteristics and multi-level regression analysis to understand the place based variation in effects of different factors on dietary diversity. We found that, depending on how "access to market" is measured, there can be significant impacts on dietary diversity, and this is mediated by farm characteristics. For small farms with already good market access, higher diet diversity is associated with cultivating larger areas and owning larger livestock holdings, but not with easier market access. For isolated larger farms with a focus on livestock production, higher diet diversity is associated with easier market access (i.e., proximity to road), as well as greater livestock diversity. For medium-sized farms with good market access, diet diversity is mildly correlated with easier market access (i.e., proximity to road) but significantly associated with greater crop diversity. The need to account for place-based mediating effects is clearly important and highlights an exigency for greater use and development of localized models that can capture the extent to which effects might change when contexts change.

KEYWORDS

market access, food systems, agriculture, smallholders, multi-level modeling, Bayes' theorem, Bayesian

Introduction

Despite significant food security improvements, ∼800 million people are still chronically hungry and over 2 billion people suffer from malnutrition (FAO, 2018). Africa and Asia are home to a significant share of undernourished people, many of which are smallholder farm households engaged in agriculture (Nandi et al., 2021). The self-consumption of on-farm produce is typical among such households, leading some studies to conclude that greater production diversity leads to better household dietary diversity (Snapp and Fisher, 2015; Jones, 2016; Ickowitz et al., 2019) whilst others find the contrary, that greater specialization raises incomes and dietary diversity (Sibhatu et al., 2015). Dietary diversity, defined as the number of unique foods consumed over a given period of time (IFPRI, 2002), is a widely accepted proxy indicator of broad nutritional status (Verger et al., 2019). At the same time, understanding the degree of on-farm diversification/specialization, defined as the number of unique agricultural products produced (e.g., crop species, livestock breeds), best suited to maximize a households dietary diversity will contribute toward greater food security (Thornton and Herrero, 2014), which is a major development objective.

Smallholders are rarely strictly subsistence-oriented nor wholly market-oriented, as there is almost always some level of inseparability between farm production and food consumption. Market catchments are diverse and across geographies are expected to have differing social norms, consumer preferences, or opportunities to participate as consumers and sellers, all of which define the level of market functionality (Nandi et al., 2021). If markets function poorly then production and consumption decisions are "non-separable" (i.e., foods produced and consumed are identical), whilst well-functioning markets allow such decisions to be "independent" (i.e., food production has no influence on household food consumption) (Nandi et al., 2021).

Whether pursuing diversified or specialized farm strategies, smallholders can utilize markets at any point in the crop cycle, and prior to planting they are likely to consider the desired level of market orientation for maximizing their utility (Davidson and Kropp, 2017). Studies have reported that where agro-ecological conditions are good and markets are functioning well, then farm production diversity becomes less important for dietary diversity (Sibhatu and Qaim, 2017). In these instances, improving market access and specialization are more effective strategies for increasing dietary diversity than increasing on-farm diversity, which could likely reduce incomes due to the lost benefits of specialization (Sibhatu et al., 2015). In apparent contradiction, several studies show the relationship between farm production diversity and dietary diversity to be positive, particularly when market access allows for high quality agricultural inputs to be purchased (Snapp and Fisher, 2015; Bellon et al., 2016). Furthermore, studies find that high levels of specialization can lead to reduced food security at the foodshed level, manifesting in instances of smallholders having higher incomes but lower dietary diversity (Jones, 2016; Ickowitz et al., 2019).

The decision to produce food on-farm or to purchase it from market is complex, has important implications for dietary diversity and, given the heterogeneous nature of markets and context specificity, is difficult to assess (Nandi et al., 2021). There are multiple possible indicators for market access including (a) distance to market (the most commonly used indicator), (b) travel time to market, (c) travel time to nearest town, (d) household ownership of mode of transport, (e) household distance from milk collection center, (f) walking time to district-level market, (g) transportation costs, (h) market participation, (i) distance to population center, (j) proportion of food purchased, (k) distance to nearest paved road, and (l) access to market information (Nandi et al., 2021). In an exploration of the effectiveness of common market access indicators, Chamberlin and Jayne (2013) found few correlations between them, and concluded that no single definition of market access captures all local market access dimensions, therefore advocating a more nuanced and context-specific approach to measuring market access.

Kenya exemplifies this situation as its agricultural sector is dominated by smallholders that often have to tackle this question of diversification and market-orientation for their livelihoods and food security (Wilkus et al., 2019). Kenya has a large variation in climatic and socio-economic conditions, resulting in a mosaic of agroecological and market opportunities, as well as constraints (Bryan et al., 2013). This makes it an interesting study context to try and disentangle the effects of different drivers of food security across different scales. Furthermore, Kenya is representative of how several countries in East and Southern Africa are developing rapidly from an economic perspective, while population growth rates are high. Food insecurity and hunger remain huge problems especially in its rural areas, where agriculture is the backbone of the local economy (Bryan et al., 2013). In this study we focus on farming communities in South and West Kenya that share these general characteristics, but also have a good availability of a wide range of geo-referenced farm household characteristic data, as well as data needed to construct market access indicators.

The objective of this study is to assess if the role of market access, and other farm-household characteristics, in relation to dietary diversity can be meaningfully interpreted in a quantitative and spatially heterogeneous manner. As yet, no holistic measure of market access has been agreed (Nandi et al., 2021). For this reason, and in order to capture a variety of routes to market this study has included two market access indicators: (a) the walking time from household to nearest road ("time to road") and (b) the drive time to market from the nearest road ("drive time to market"). Neither indicator aims to capture market participation or market quality, but whilst still imperfect we do attempt to provide a community-wide and non-product specific assessment of two dimensions of market access: (a) access to physical market locations ("drive time to market") and (b) access to traveling marketing agents ("time to road"). Whilst a study in a specific locality will generally produce one set of parameter values showing which is the most effective dietary diversity strategy within that study location, a meta-analysis across multiple locations can smooth and average out the differences, and generally identify whether any of these strategies works reliably. In response, we employ a multi-level logistic regression model that provides probability distributions for each variable and are location sensitive.

Methodology

Research approach

Due to the intricacy of the topic a relatively complex and multistage methodology has been used. Figure 1 outlines the different methodological steps undertaken in this study. Here we rely on secondary data collected by the Rural Household Multi-Indicator Survey (RHoMIS) open-access dataset (van Wijk et al., 2020). After extracting and treating the data for the relevant study region (Section Data collection) we estimate a dietary diversity indicator (Section Dietary diversity). Subsequently based on the decision of six relevant farm household characteristics (see below) we constructed two market access indicators (Section Market access). Households were then separated into clusters based on geographical proximity before model construction (Section Multilevel logistic regression).

The selection of the six smallholder farm household characteristics used here to describe farm configuration was guided by a literature review (Ellis, 1998; Chamberlin and Jayne, 2013; Wiggins and Keats, 2013; Castello et al., 2015; Bellon et al., 2016; Qaim et al., 2016; Koppmair et al., 2017; Ickowitz et al., 2019) and refined through an additive approach in the model construction. Below we introduce briefly the six selected characteristics.

"Crop Diversity" is the number of crop species grown and is a prominent factor influencing dietary diversity (Snapp and Fisher, 2015; Bellon et al., 2016; Qaim et al., 2016; Sibhatu and Qaim, 2017; FAO, 2018; Ickowitz et al., 2019). "Livestock Diversity" is the number of livestock types kept with no distinction between draft and non-draft animals. Diversification is a central livelihood strategy for millions of rural households (Bellon et al., 2016) and is often seen as an immediate way to improve dietary diversity (Nandi et al., 2021). Diversification and commercialization are not binary, Conelly and Chaiken (2000) found that can go hand-in-hand *via* intercropping farming methods, whereby subsistence crops suitable for human and animal consumption are grown alongside cash-crops such as coffee, tea and French-beans.

"Land Cultivated" is the total area of land (whether rented or owned) farmed by a household measured in hectares. A study in India by Kadiyala et al. (2014) finds farm size is more important for determining dietary diversity than crop diversity, but this is specific to context. Frelat et al. (2015) suggest a farm of 0.4 ha is enough to feed a household of 4.4 Male Adult Equivalent (MAE) in sub-Saharan Africa, although if the household is isolated from markets more land would be required. Farm size can also influence foodshed diversity, as landscapes of many small farms produce a wider variety of nutrients than landscapes of large mono-culture farms (Herrero et al., 2017).

"Livestock Holdings" is the total livestock owned measured in Tropical Livestock Units (TLUs) (FAO, 1993). Higher livestock ownership has been found to improve dietary diversity but with diminishing returns after 0.2 TLUs (Frelat et al., 2015). Ownership of small livestock is more positively associated with dietary diversity than ownership of large livestock (Azzarri et al., 2015).

"Household Size" is the number of members of the household measured in MAE. Household members are an important source of on-farm labor but, depending on the household's assessment of marginal return, can also be used to generate off-farm and non-farm income. Overall, household size and dietary diversity tend to be negatively correlated, but this can vary depending on where household members are employed (Abafita et al., 2016).

"Total Income" is the sum of all cash incomes earned by a household, calculated by adding the annual household income from crop sales, livestock sales and off-farm incomes. Household members can generate off-farm and non-farm income through the sale of their labor, which has been found to be positively correlated to dietary diversity, particularly if controlled by a female household head (Koppmair et al., 2017).

Study sites

The study households were located in 10 counties located in (a) southern Kenya (Kitui and Makueni counties), (b) west-central (Baringo county), and west Kenya (Migori, Homa Bay, Kericho, Kisumu, Vihiga, Siaya, and Busia counties). Climatic conditions in both of the southern Kenya counties range between Arid Steppe and Equatorial Desert (Kottek et al., 2006) providing a hot, arid environment. The road network in Kitui county is sparse compared to Makueni county, which is connected south-east to north-west by the Mombassa-Nairobi Expressway. Climatic conditions in the west-central county (Baringo) are also classified as Equatorial Dessert (Kottek et al., 2006), with a sparce road network containing few paved roads, and a steep terrain with elevations > 2,500 m. Finally, all seven of the western study counties are located on the shores of Lake

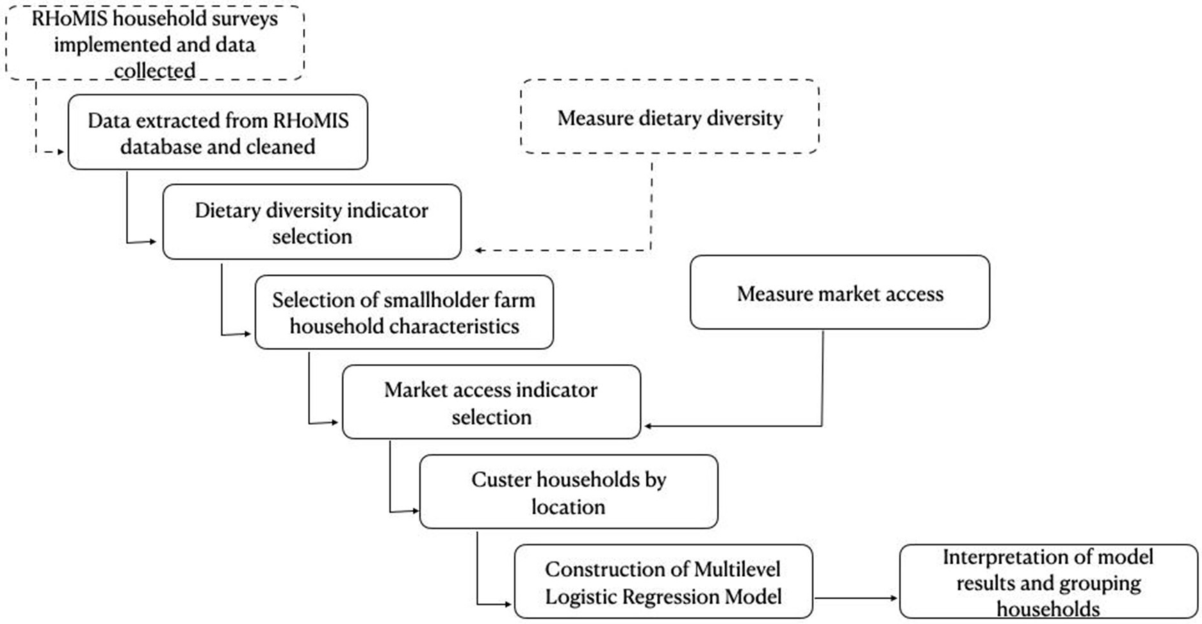

FIGURE 1
Flow diagram denoting each stage of the methodology. Dashed lines indicates process or decision outside the control of the study.

Victoria, with the climate categorized as Equatorial Fully Humid (Kottek et al., 2006), and a road network that is dense but mostly unpaved.

Households within these study areas are dispersed across four farming systems: (a) maize mixed, (b) pastoral, (c) agropastoral, and (d) highland perennial. Each farming system is defined as a population of farm households of mixed types and sizes that have broadly similar patterns of available/used resources, livelihoods, consumption patterns, and relevant constraints and opportunities (Dixon et al., 2021).

The majority of study households (591 households, Section Data collection) are classified as within a maize mixed system, a predominantly sub-humid agroecological zone with a crop growing season of about 6 months. Households are located in an average altitude of around 1000 meters above sea level, and experience a rainfall regime that follows a bimodal pattern, contributing to the long crop growing season. Maize dominates their cropping systems, but there is also cash-cropping, often coffee, tea, fruit and vegetables (Dixon et al., 2021).

Approximately 180 households are within a pastoral farming system and 50 households are within an agropastoral farming system. Pastoral systems are predominantly within the tropical warm arid agroecological zone whilst, agropastoral systems are predominantly within the tropical warm semi-arid zone. Again, rainfall in these systems tends to be bimodal, which spreads the growing season over a long period but with high inter-annual rainfall variation. This in turn leads to high inter-annual variation in forage available to herders, and a severe mid-season dry spell that can disrupt pollination and negatively impact crop yields. Soils in these systems tend to be of low quality, both poor in nutrients and physical properties (Dixon et al., 2021).

Finally, there are 93 households located within a highland perennial system, a predominantly tropical cool subhumid agroecological zone. It is characterized by a long growing season, relatively fertile volcanic soils, and generally plentiful water. Consequently, population densities in this system tend to be very high, reaching up to 1,000 persons/km^2 (Dixon et al., 2021).

It should be mentioned that the distribution of study households across farming systems does not follow exactly the geographical distribution of the sample. In other words in each study region the study households fall in a combination of different farming systems.

Data collection

In this study we use household survey data collected from the Rural Household Multi-Indicator Survey (RHoMIS) open-access dataset (van Wijk et al., 2020). The questionnaire tool has been applied across smallholder farming systems in Africa, Asia, and Latin America, to collect geo-located farm-livelihood characterization data and standardized dietary indicators (Hammond et al., 2017). Responses are collected *via* trained enumerators who spend 40–60 min surveying each household. The RHoMIS data has been widely used by researchers in academic and NGO communities and is considered a robust data source (Fraval et al., 2019b).

The households included in this study were interviewed in three tranches between late 2016 and early 2017. Data collected in 2016 was part of the Africa and South-East Asia wide CCAFS project, IMPACTlite. We sampled 160 households in each of Wote, Makueni County, and Kap Sarok, on the Kisumu County-Kericho County border. Data collected in early 2017 was part of the Ethiopia, Kenya, Tanzania wide SAIRLA project, led by Bioversity International. Over 300 households were interviewed in Kenya, with 192 located in Kitui County and 123 in Makueni County. The remaining 396 households were also interviewed in early 2017, and were part of the ICRAF project SCAN. All data collection exercises conducted random sampling of smallholder farm households within the selection study sites in order to capture the full heterogeneity of farming systems and geographies.

RHoMIS data collection conforms to the principals of the 1964 WMA declaration of Helsinki, they are processed in an anonymised way and no household identification variables are published within this study. For each application of RhoMIS the research was approved by the lead institutions research ethics review board, and in each case informed consent was received from the respondents prior to beginning the interview, with the respondents able to skip questions or cancel the interview at any time. Written approvals were not collected due to respondents' poor literacy and their quite reasonable mistrust of signing documents which they could not understand (van Wijk et al., 2020).

Overall, in terms of geographic distribution the subset of the RHoMIS dataset used here incorporated 914 households from ten counties in Southern and Western Kenya.

In total 408 households were located in Southern Kenya, split between the Makueni (296 households) and Kitui (192 households) counties.

In west-central Kenya, 192 households were located in Baringo county.

The remaining 351 households were located in west Kenya, and split between: Migori (7), Homa Bay (56), Kericho (100), Kisumu (62), Vihiga (44), Siaya (22), Busia (35).

We should note here that RHoMIS data collection conforms to the principals of the 1964 WMA declaration of Helsinki. They are processed in an anonymised way and no household identification variables are published within this study. For each application of RhoMIS the research was approved by the lead institutions research ethics review board, and in each case informed consent was received from the respondents prior to beginning the interview, with the respondents able to skip questions or cancel the interview at any time. Written approvals were not collected due to respondents' poor literacy and their quite reasonable mistrust of signing documents which they could not understand (van Wijk et al., 2020).

Data analysis

Dietary diversity

Dietary diversity was measured using an adapted version of the Household Dietary Diversity Score (HDDS) (FAO, 2013), also used and described in detail in Fraval et al. (2019a); Fraval et al. (2020) and Ritzema et al. (2019). The indicator is a categorical variable calculated by tallying the number of food groups (from a standardized list of 10 food groups), that a household has consumed over a 4-week recall period and indicating whether that food group was consumed "daily", "weekly", "monthly" or "never/less than monthly" (Hammond et al., 2017). Food groups consumed monthly, less than monthly, or never are given a score of 0 whilst food groups consumed on at least a weekly basis are given a score of 1, with a maximum achievable score of 10.

As this is an adaptation of the standard HDDS definition, the results in this study only indicate the variation in dietary diversity in the population sample and not household nutrition (Verger et al., 2019). Household dietary diversity scores were collected for both the "good season" (mean HDDS 6.0; std 2.3) and the "lean season" (mean HDDS 4.2; std 2.6). All HDDS scores used in this study are "lean season" only as this is generally the time of lowest dietary diversity (Bellon et al., 2016) and the time when markets are most important for alleviating food scarcity (Nandi et al., 2021). Data for other variables are not disaggregated by season.

Market access

Market orientation and market participation offer two alternative, non-spatial, proxies for market access. Market orientation assesses the ratio of the quantities of farm inputs purchased and agricultural outputs sold at market. Conversely market participation captures the quantity of production excess that a smallholder sells at market. Market orientation identifies a premeditated commercial decision by households wishing to use markets as a cornerstone of food security, whilst market participation reflects markets being used as a source of cash, a practice common in the lean season (Wilkus et al., 2019). Both of these metrics are highly susceptible to seasonal variations (Abafita et al., 2016).

Whether using a market access proxy (e.g., "distance to nearest town") or an alternative such as market orientation or market participation, it seems reasonable to agree with Chamberlin and Jayne (2013) that indicators of market access are not always highly correlated with one another. It has been argued that a more nuanced and spatially differentiated understanding of the role of market access on top of well-known micro-level effects of farm (e.g., crop diversity, land holdings, livestock holdings) and household (e.g., access to off farm income, family size) characteristics in achieving diverse diets would help in planning data-led development strategies

(Ruel et al., 2018). Consequently, in this study we used two measures of market access. "Time to Road" estimated as the euclidean distance from household to nearest road, assuming a walking speed of 1.4 m/s with no allowances for topography, individual's physical capacity or use of bicycle or other transport method. "Drive Time to Market" that estimated journey time from households nearest road to the most convenient market. This latter metric assumes the use of motorized transportation traveling at the speed limit for that road, but making no allowance for congestion or seasonal reductions in road quality. Times were calculated using Opens Source Route Mapper and OpenStreetMap's road network for Kenya.

Multilevel logistic regression

In this study we use a Multilevel Logistic Regression (MLR) to accommodate the spatially varying relationships between dietary diversity and factors of smallholder farm strategy. This multilevel approach allows each effect to vary depending on its geographic place (Arcaya, 2012). At each place the effect of each variable is determined by both the data at that place and, to maintain statistical power, "pooled" data from similar households at other places (Gelman, 2006). Multilevel models are the mainstay of machine learning (Hoffman and Gelman, 2011) and provide probability distributions for predictions or estimates at each place as opposed to a single prediction or estimate. This paper contributes a case study for multilevel model use within the rural development context of a developing county.

To populate the model we used geo-tagged household survey data, and market locations, calculated realistic journey times, and explored patterns of market use among smallholders in rural South and West Kenya as outlined in Sections Data collection, Dietary diversity, and Market access. We assessed the effect of market access on household dietary diversity, whilst also taking account of on-farm production systems. In this sense this study outlines a new methodological approach that was made possible by advances in techniques for measuring household dietary diversity (HDDS) (Section Dietary diversity) and developments in open source network analysis (Open Source Route Mapping, OSRM) technologies (Section Market access).

Multilevel models are "placial," not spatial, which means that places used within the model must be specified a priori (Arcaya, 2012). However, we only had information about the locations of surveys taken, with no reliable indicators of the geographic extent of the foodshed in which the sample was taken. Most households in the RHoMIS dataset did include a variable indicating the village name, but this was proved to be unreliable in the sense that there were many responses in the same geographical area with different village names.

Therefore, we first needed to cluster the survey responses into "places" that correspond to small communities where food and farming decisions are more likely to be similar. Using DBSCAN (Ester et al., 1996; Schubert et al., 2017; Arribas-Bel et al., 2019) we grouped the surveyed households into 12 clusters, which became our "places" (see Figure 2). Due to the dispersion between places and the sampling strategy of RHoMIS, we set the DBSCAN "separation" parameter (ε) (the straight-line distance between points beyond which data is not considered linked) to 15,000 m. This indicates the maximum distance at which a pair of sites can be considered as "nearby" in the algorithm. Further, in light of information about the sample design, we restricted communities to be of 4 or more respondents (setting *minPts* equal to one returns the same clustering). With these communities, we constructed place-based estimates of the relationship between our explanatory factors and diet diversity.

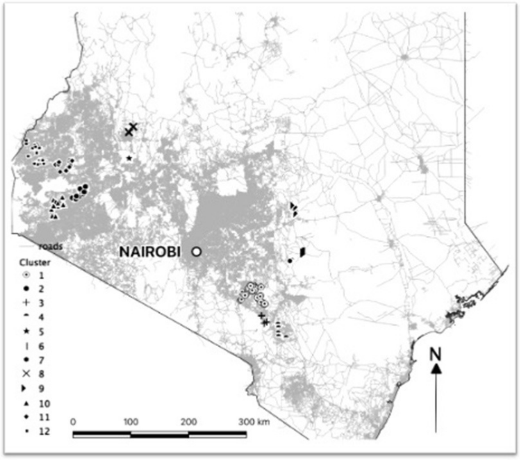

FIGURE 2
Survey locations by cluster. Gray shading indicates roads. Symbols indicate survey locations and cluster.

Bringing variables and clusters together the Bayesian MLR model is defined through Equation (1) as:

$$
\begin{aligned}
ßHDDS_i = {} & ß_{ji}Cluster_i + ß_{ji}TimetoMarket_i + ß_{ji}TimetoRoad_i \\
& + ß_{ji}CropDiversity_i + ß_{ji}HouseholdSize_i \\
& + ß_{ji}LandCultivated_i + ß_{ji}LivestockHoldings_i \\
& + ß_{ji}LivestockDiversity_i + ß_{ji}TotalIncome_i \qquad (1)
\end{aligned}
$$

Where

i is an index denoting a specific survey response,

j is an index describing the place a survey response occurs, and

ß is the effect of the variate on household diet diversity.

This is a "varying-slope" multilevel model (Gelman and Hill, 2006), which allows the relationship between our variables and the response to change depending on the place (*j*). Thus, we may get one effect for "Time to Market" in one place, and a different effect in another. Varying-slope multilevel models are useful precisely because they can provide estimates of an "overall" effect, while also recognizing that local deviations from the overall effect can make a significant impact on the outcomes in that area.

Results of the regression model for each cluster identified a smaller number of household groups. The groups were composed of clusters which showed similar responses in the model. Membership of each group was based primarily on the similarity of experience of market access variables. Membership was then refined further, based on similarities across other livelihood variables.

Results

Descriptive statistics

Descriptive results for each of the 12 clusters are presented in Table 1. Across the survey population median dietary diversity is five suggesting moderate levels of diet diversity, but it varies significantly between clusters. Clusters 1, 2, 5, 8, 10, and 11 are dominated by households with high dietary diversity (average dietary diversity scores > 5) whilst households with low dietary diversity (average dietary diversity scores < 5) are the majority in clusters 4, 6, and 7.

The average "Drive Time to Market" was around 20 min, although the majority of the clusters reported times that were below this average. Conversely Clusters 5 and 9 were notably more isolated, with average "Drive Time to Market" of $>$40 min. A similar trend was found for the variable "Time to Road". Whilst the average walking time from house to nearest road is about 8 min, most clusters were within a 5-min walk. Clusters 6 and 7 were much more isolated with a walk of over 20 min to the nearest road.

Clusters exhibited different farm characteristics. Growing a range of crops on-farm is common and the average "Crop Diversity" across the survey population was four crop species. However, this varied greatly between clusters. For example, no households in Clusters 10, 11, and 12 reported growing any crops, whilst households in Clusters 1, 2, 5, and 8 generally grew five or more crop species.

All households reported owning livestock, but the actual variety and quantity varied considerably. Whilst households in Clusters 10, 11, and 12 tended to specialize on one livestock type, households in Clusters 1, 2, 3, and 5 have diversified livestock species ownership and generally owned three livestock species. "Livestock Diversity" for households in the remaining clusters averaged two species. There was clearly a livestock focus among households in Clusters 5 and 6, where holdings averaged over 20 TLUs. Conversely, households in Clusters 1, 11, and 12 have much smaller livestock holdings ($\sim$2.5 TLUs). The remaining households generally owned between 4 and 6 TLUs although households in Cluster 7 averaged $>$9 TLUs.

The area of land cultivated by most households was small ($<$2 ha). The exceptions were households in Clusters 1, 6, 7, and 9, which averaged 3 ha or 4 ha in the case of Cluster 6. Household size across the survey population was broadly consistent, at or around 6 Male Adult Equivalents (MAEs). Larger households tended to be found in Clusters 3 and 4, whilst smaller households were more common in Clusters 1 and 2.

Households "Total Income" averaged USD 1,546 for the whole survey population, but there was variation by an order of magnitude across the clusters. The highest earning were reported by households in Cluster 6, where incomes averaged almost USD 3,500. Annual household incomes for the households in both Clusters 5 and 7 were also high and averaged over USD 2,500. By contrast, households in Cluster 1 and 8 reported incomes below USD 1,000. The remaining households generally reported incomes between USD 1,000–2,000.

Inferential results

Model results for all 12 clusters are presented in Table 2 and Figure 3, whilst the statistical significance of the results are presented in Figure 4. For each independent variable the "Odds" value represents the estimated change in HDDS given a unit change in that variable. For example, if "Time to Market" is reduced by 1 min for households in Cluster 6 then the likelihood of their HDDS rising by one point is estimated to increase by 4%, or put another way, their HDDS is estimated to rise by 1/25th. Table 2 rows "2.5" and "97.5" are confidence intervals and provide guidance on the significance of model results, i.e., if both "2.5" and "97.5" share the same sign then the results are statistically significant (see heat map in Figure 4). Continuing the above example, in that case the confidence intervals are -7 to -1%, which means the findings are statistically significant. However, if confidence intervals span above and below zero then findings are statistically insignificant. For example, "Livestock Diversity" confidence intervals for households in Cluster 5 are -2 and $+2$% with an estimated odds change of zero. Figure 4 visualizes the direction of effect and the statistical significance of findings in either dark red or dark green depending on whether it is negative or positive. Statistically insignificant findings are colored light green if the average odds estimate is positive and light red if the average odds estimate is negative.

Market access

Reducing ***"Drive Time to Market"*** by 1 min improves the odds of increasing a household's HDDS in only two clusters (Clusters 4 and 7), although confidence intervals suggest the effect is statistically weak (Figure 4). For five clusters (Clusters 2, 6, 9, 10, and 11) the overall effect is statistically insignificant, whilst for households in Cluster 1, 3, 5, 8, and 12 a shorter "Drive Time to Market" is actually associated with a lower HDDS. This

TABLE 1 Descriptive statistics for the main study variables for the 12 clusters.

Cluster		1	2	3	4	5	6	7	8	9	10	11	12
No. households		222	162	16	50	93	46	56	70	78	36	40	45
HDDS		6	7	4.5	2	6	2	3	5.5	4	7	6	4
Drive time to market	Minutes	16	10	11	13	54	18	14	11	40	11	5	8
	Std	9	5	8	6	3	4	5	5	13	6	3	5
Time to road	Minutes	5	3	0	8	9	28	23	1	14	3	2	3
	Std	9	3	0	8	8	18	6	1	16	3	3	3
Crop diversity	Count	5	5	4	3	5	3	3	6	4	0	0	0
	Std	2	3	2	1	2	1	1	2	1	0	0	0
Livestock diversity	Count	3	3	3	2	3	2	2	2	2	1	1	1
	Std	1	1	1	1	1	1	1	1	2	0	0	0
Livestock holdings	TLUs	2.5	4.4	5.7	4.2	23.9	21.4	9.1	5.9	4.7	4.4	2.5	2.5
	Std	2.4	3.8	2.6	7.3	18.7	23.9	11.4	5.9	7.3	3.1	2.3	2
Land cultivated	Hectares	3	2	2	2	2	4	3	1	3	1	1	0.5
	Std	3	1	1	1	1	2	1	1	2	1	0	0
Household Size	MAE	5	5	8	7	6	6	6	6	6	6	6	6
	Std	3	2	4	5	3	3	3	3	2	3	2	3
Total income	US$	775	1,593	1,195	1,102	2,629	3,436	2,717	975	1,316	1,633	1,774	1,187
	Std	1,126	1,600	750	2,006	2,155	2,621	2,942	1,120	1,883	2,121	1,668	1,508

For each variable the mean and standard deviation are reported.

suggests that "Drive Time to Market" may not have a consistent impact on diet diversity across the different kinds of places we analyzed.

Reducing ***"Time to Road"*** by 1 min improves the odds of an increased HDDS for households in five Clusters (1, 4, 5, 6, and 9), the majority of which are around a 10-min walk to nearest road. The impact of a change in "Time to Road" is minimal for households in six clusters (Clusters 2, 3, 8, 10, 11 and 12), where most households are already within a 3-min walk to the nearest road. Households in Cluster 7 are over a 20-min walk from a road, but model results do not suggest that closer proximity increases dietary diversity.

Farm household characteristics

Increasing ***"Crop Diversity"*** by one crop species is likely to improve the odds of an increase in HDDS for households in five clusters (Clusters 1, 2, 3, and 8) that already tend to grow a diverse selection of crops (>4 crop species). For households in five clusters (Clusters 4, 5, 6, 7, and 9) where average "Crop Diversity" ranges from 0 to 5, a higher crop diversity is actually associated with a lower HDDS, while for households in the remaining clusters our results are statistically insignificant (Figure 4). This suggests that the impact a change in "Crop Diversity" has on a household's dietary diversity, also varies across the different places we have analyzed.

Increasing ***"Livestock Diversity"*** by one animal species could improve the odds of an increase in HDDS for households in seven clusters (Clusters 2, 4, 5, 6, 7, 8, and 9) that tend to already own two livestock species, but the confidence intervals suggest the effect is inconsistent. For households with higher livestock diversity (~3 livestock species), which are generally found in Clusters 1 and 3, this higher diversity is associated with lower household dietary diversity, but again, confidence intervals do not suggest a consistent impact for all households. For households in Clusters 10, 11, and 12 the overall effect of "Livestock Diversity" is statistically insignificant. Overall, this suggests that across the places we analyzed, the diversity of livestock owned has a usually positive but inconsistent impact on household dietary diversity.

Increasing ***"Livestock Holdings"*** by 1 TLU is likely to improve the odds of an increase in HDDS for households in Clusters 1, 2, 10, 11, and 12, where holdings are generally at or below 4.4 TLUs. For households in all other clusters "Livestock Holdings" are usually > 4.4 TLUs and the odds of higher dietary diversity are either statistically insignificant or negative. Across the places we analyzed, "Livestock Holdings" appear to have diminishing returns for household dietary diversity and may even turn negative when it is >4.4 TLUs.

Expanding ***"Land Cultivated"*** by 1 ha is likely to improve the odds of an increase in HDDS for most households in eight clusters (Clusters 1, 2, 5, 8, 9, 10, 11, and 12) with the effects particularly significant when the area cultivated is <1 ha.

TABLE 2 Odds ratio of the effect of different variables to dietary diversity for each cluster.

Cluster		1	2	3	4	5	6	7	8	9	10	11	12
Intercept	Odds	−13%	336%	74%	−43%	45%	−51%	−73%	29%	−33%	31%	38%	47%
	2.5	−73%	41%	−63%	−87%	−78%	−94%	−96%	−61%	−86%	−61%	−66%	−61%
	97.5	194%	1459%	1408%	112%	871%	131%	26%	395%	180%	456%	546%	503%
Drive time to market	Odds	4%	0%	3%	−2%	2%	0%	−1%	2%	0%	0%	0%	3%
	2.5	*1%*	*−4%*	*−4%*	*−9%*	*−1%*	*−7%*	*−7%*	*−3%*	*−3%*	*−6%*	*−11%*	*−3%*
	97.5	*7%*	*5%*	*13%*	*4%*	*7%*	*6%*	*4%*	*8%*	*2%*	*7%*	*10%*	*19%*
Time to road	Odds	−2%	1%	−1%	−4%	−1%	−4%	1%	0%	−1%	1%	2%	1%
	2.5	*−5%*	*−4%*	*−14%*	*−11%*	*−5%*	*−7%*	*−4%*	*−8%*	*−3%*	*−7%*	*−6%*	*−6%*
	97.5	*0%*	*9%*	*9%*	*1%*	*2%*	*−1%*	*7%*	*9%*	*1%*	*12%*	*17%*	*16%*
Crop diversity	Odds	15%	4%	35%	−3%	−5%	−22%	−13%	10%	−9%	−3%	−3%	1%
	2.5	*−1%*	*−5%*	*−7%*	*−32%*	*−20%*	*−57%*	*−43%*	*−5%*	*−33%*	*−52%*	*−56%*	*−49%*
	97.5	*34%*	*16%*	*144%*	*37%*	*9%*	*8%*	*11%*	*32%*	*12%*	*68%*	*81%*	*84%*
Livestock diversity	Odds	−5%	6%	−2%	1%	1%	7%	6%	1%	4%	0%	0%	0%
	2.5	*−25%*	*−7%*	*−42%*	*−19%*	*−15%*	*−14%*	*−11%*	*−19%*	*−10%*	*−34%*	*−39%*	*−35%*
	97.5	*12%*	*35%*	*37%*	*36%*	*31%*	*91%*	*68%*	*37%*	*37%*	*55%*	*63%*	*59%*
Livestock holdings	Odds	20%	5%	−14%	−11%	0%	1%	1%	4%	2%	22%	32%	12%
	2.5	*6%*	*−3%*	*−36%*	*−24%*	*−2%*	*−2%*	*−4%*	*−4%*	*−3%*	*3%*	*2%*	*−14%*
	97.5	*36%*	*14%*	*8%*	*−2%*	*2%*	*4%*	*6%*	*11%*	*8%*	*46%*	*84%*	*65%*
Land cultivated	Odds	15%	18%	−42%	−30%	9%	−18%	−3%	6%	20%	52%	80%	25%
	2.5	*4%*	*−2%*	*−78%*	*−53%*	*−15%*	*−36%*	*−27%*	*−27%*	*−3%*	*−11%*	*−8%*	*−37%*
	97.5	*28%*	*44%*	*5%*	*−2%*	*43%*	*1%*	*27%*	*54%*	*51%*	*256%*	*489%*	*239%*
Household size	Odds	−6%	2%	−3%	1%	0%	3%	0%	0%	−1%	1%	1%	0%
	2.5	*−14%*	*−5%*	*−16%*	*−6%*	*−7%*	*−5%*	*−9%*	*−8%*	*−10%*	*−8%*	*−10%*	*−10%*
	97.5	*0%*	*12%*	*6%*	*10%*	*8%*	*20%*	*9%*	*8%*	*7%*	*17%*	*17%*	*15%*
Total income	Odds	1%	1%	1%	1%	0%	1%	1%	0%	0%	0%	0%	0%
	2.5	−1%	−1%	−2%	−1%	−1%	0%	0%	−1%	−2%	−2%	−2%	−2%
	97.5	3%	2%	6%	4%	2%	4%	3%	3%	0%	2%	4%	3%

For each independent variable the "Odds" value represents the estimated change in HDDS given a unit change in that variable. If a variable is changed by 1 unit then the likelihood of a households HDDS changing by 1 point is estimated and presented as a percentage. For example, +100% would be a 1 unit increase in HDDS. Rows "2.5" and "97.5" denote the confidence intervals and provide guidance on the significance of model results.

Conversely, for households in three clusters (Clusters 3, 4, and 6) a 1 ha increase in "Land Cultivated" is likely to reduce the odds of an improved HDDS despite households in Clusters 3 and 4 generally cultivating small areas of land (∼2 ha). For households in Cluster 7 our findings are statistically insignificant. This suggests that "Land Cultivated" has a generally positive impact on household dietary diversity, but can vary across the places we analyzed.

The overall effect of ***"Household Size"*** on household dietary diversity is statistically insignificant for households in all clusters with the exception of Cluster 1. For these households, a 1 MAE increase in "Household Size" is estimated to reduce the odds of an improvement in dietary diversity.

Increasing ***"Total Income"*** by USD 100 is likely to improve the odds of an increase in HDDS by <1%, for households in all clusters. Confidence intervals suggest the general effect is statistically insignificant.

Household groupings and market access

Based on clusters which showed similar responses in the model, we can identify three clear groups of clusters.

Group 1 is characterized by households where higher dietary diversity is not associated with being closer to a road (i.e., Clusters 2, 8, 10, 11, and 12), with the odds of a unit increase in HDDS generally increasing when cultivating larger areas of land and owning larger "Livestock Holdings". These farms tend to be small (<2 ha) with already good market access (<3 min walk to the nearest road) and have relatively high dietary diversity scores of four or more.

Group 2 is characterized by households where higher dietary diversity is associated with being closer to a road (Clusters 4, 5, 6, and 9) and the odds of a unit increase in HDDS also increase with reduced "Crop Diversity" but greater "Livestock Diversity". Households tend to be located >8 min walk from the nearest road and cultivate relatively large areas (>2 ha), whilst

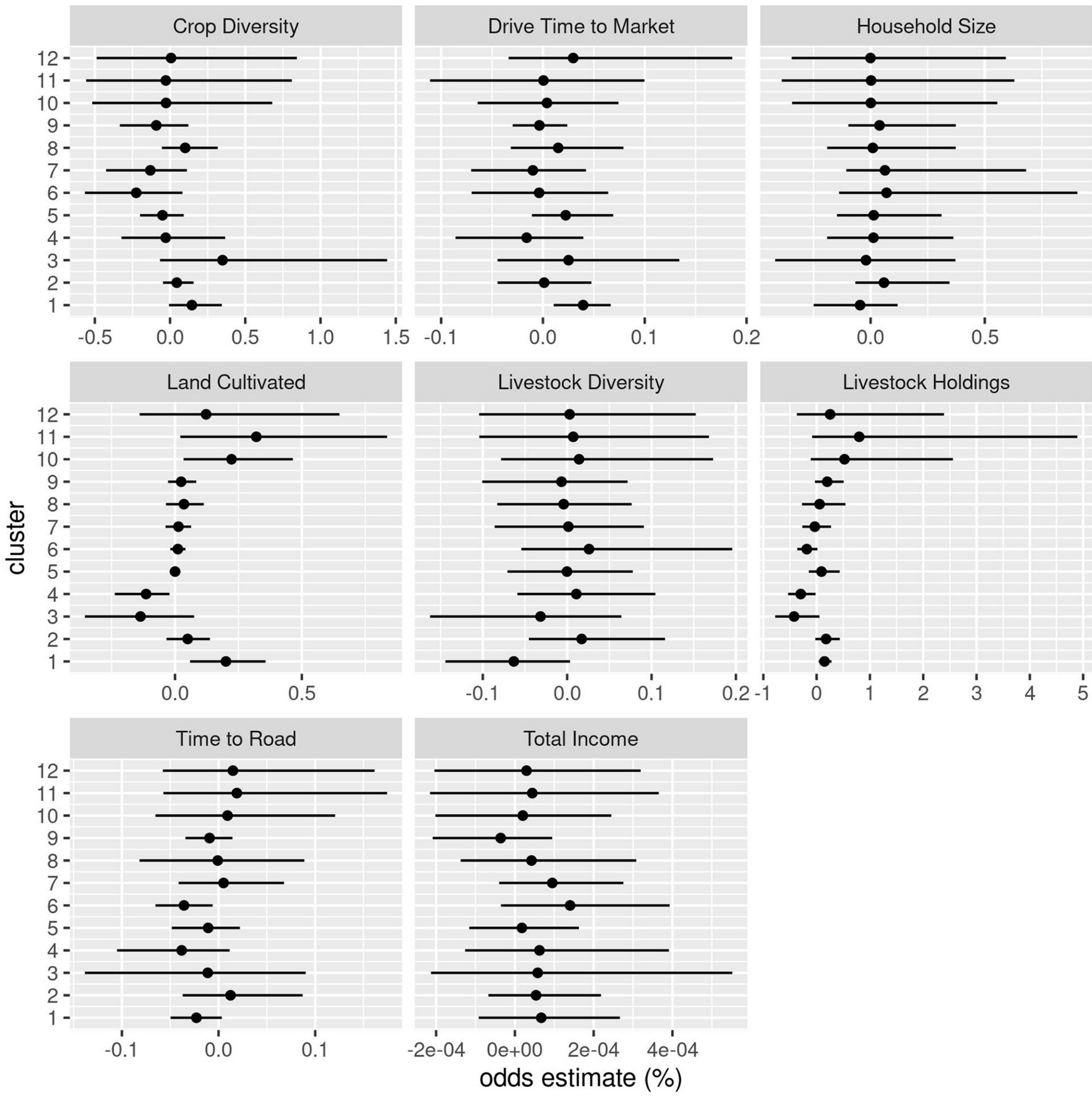

FIGURE 3
Distribution of odds of change in Household Dietary Diversity Score given an increase of one unit in each variable for each cluster. Bars not intersecting with zero denote statistically significant results. The italic values indicate the confidence intervals and provide guidance on the significance of model results.

having a livestock focus (i.e., owning more than >4 TLUs). The experience between households in these clusters is not uniform though. Households in Clusters 4, 6, and 9 tend to have a low average diet diversity (≤4 HDDS) and both low crop diversity (≤4 crop species) and low livestock diversity (≤2 livestock species). This is despite households in Cluster 6 averaging livestock holdings above 20 TLUs. By contrast, households in Cluster 5 have an average crop diversity >5, livestock diversity >3 and a high HDDS > 6.

Group 3 contains households from Clusters 1 and 3, where slightly increased dietary diversity is associated with being closer to a road but the odds of a unit increase in HDDS increase significantly with a unit increase in "Crop Diversity". These households tend to be within a 5-min walk of a road, have high diversity for both crops (more than >4 crop species) and livestock (averaging 3 livestock species) and cultivate between 1 and 3 ha of land. For households in Cluster 1, which average 2.7 TLUs, enlarging livestock holdings

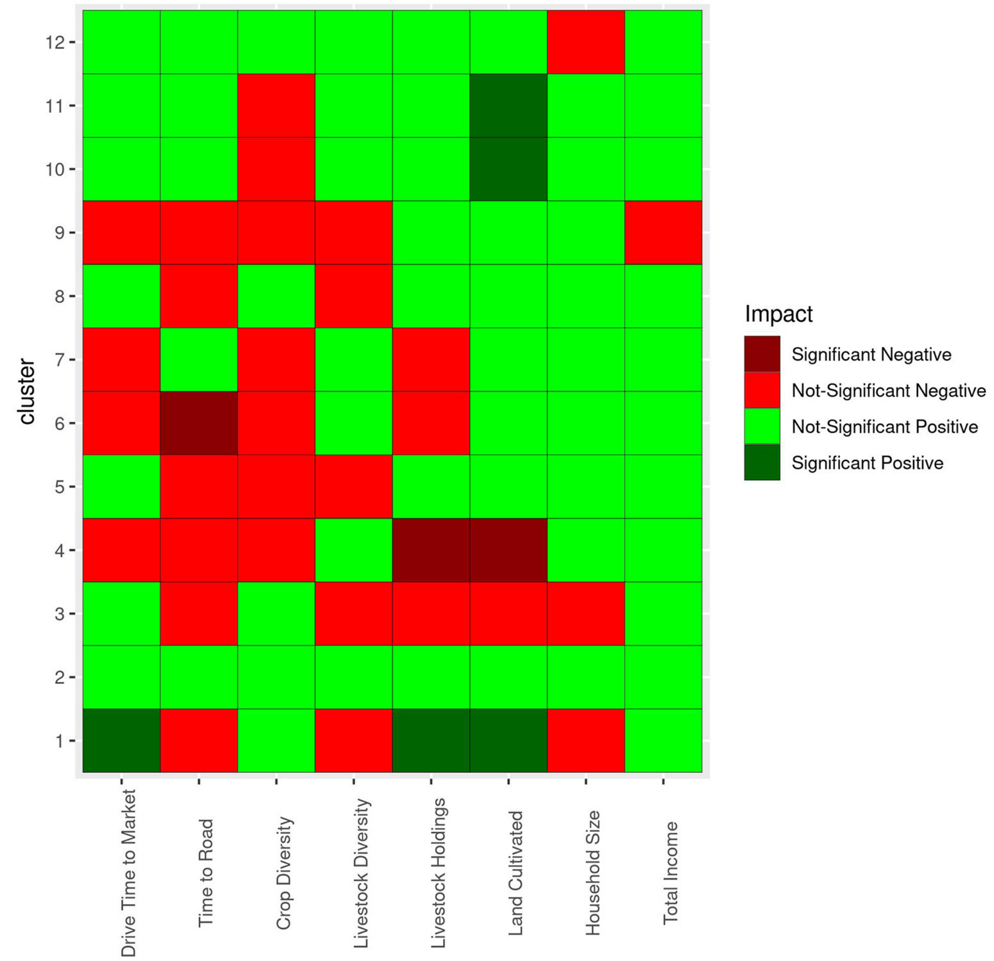

FIGURE 4
Statistical significance of the impact of each variable on the Household Dietary Diversity Score for each cluster.

has a strong positive effect on the odds of an increase in HDDS, whilst for Cluster 3 households (which average 5.7 TLUs) the opposite is true. Overall, diet diversity for Group 3 households holds-up well and they average an HDDS of five points.

The 56 Households in Cluster 7 do not fit within any of the three groupings. "Time to Road" is on average >20 min, but the households furthest from the road tend to have higher HDDS. Similarly, average "Livestock Holdings" are already large (>9 TLUs), but the households with higher numbers of livestock tend to also have a higher dietary diversity. Households that have the longest "Drive Time to Market" have the highest odds of an increase in HDDS but, counter intuitively, households cultivating smaller areas of land also have higher odds of an increase in HDDS. Whilst results appear to sit outside the literature, visual inspection of satellite imagery shows significant forest cover close to the households furthest away from the road network, which may indicate that wild food is an important dietary supplement.

Discussion

The role of market access for diet diversity

Better access to market, as indicated by the drive time from a household's nearest road to a physical market, does not generally infer increased household dietary diversity (Table 2; Figure 3). This appears to contradict the widely held view that market access ameliorates nutritional outcomes for smallholders (Stifel and Minten, 2008; Wiggins and Keats, 2013; Wilkus et al., 2019). However, this is actually consistent with findings in a number of countries including Ethiopia (Abafita et al., 2016), which show physical distance and travel time to a market location or urban areas does not have a strong effect on market use. Nevertheless, when market access was indicated by the time it takes a household member to walk to their nearest road, the effect appears to be greater, which is consistent with findings in Kenya (Chamberlin and Jayne, 2013) reporting that a reduction in walk time to the nearest road is more important than a reduction in travel times to markets for improving household nutrition. Selling produce at the farm-gate is a common marketing strategy for smallholders all over sub-Saharan Africa, as is purchasing fertilizer and other farm inputs from traveling sales agents (Yamano and Arai, 2011). In this sense, when markets are interpreted as something that can move rather than being a stationary location that farmers must commute to, then access to the nearest road could be judged as a better market access proxy than the location of the nearest market.

Toward a classification of dietary diversity strategies

Exploring household groupings reveals a mixed picture (Section Household groupings and market access). Group 1 households, which are all within a Maize Mixed farming system (Section Study sites), tended to have high dietary diversity but exhibit polarized dietary diversity strategies. Couched within the literature this might suggest that market access (i.e., proximity to road) acts as an important mediator of dietary diversity for both specialized and diversified farms. Livestock-specialized households in Clusters 10, 11, and 12, appeared to conform to the prevailing orthodox economic view that specialization increases output and thus income, which translates into improved nutrition *via* the purchase of food stuffs from markets. By contrast, the much more diverse farms in Clusters 2 and 8, fit with evidence put forward by a number of authors (e.g., Ickowitz et al., 2019) that on-farm diversity is the most effective way to improve household nutrition. What is consistent is the generally small size of farms in Group 1, which may advocate the notion that a foodshed composed of lots of small farms with reasonably good market access are much more diverse than single farms, and can consequently produce a wider variety of nutrients than a landscape of mono-culture farms (Herrero et al., 2017). Indeed, model results for Group 1 households do not suggest that greater on-farm diversity has significant impact on dietary diversity. Instead, the households in this group with the most diverse diets tended to cultivate larger areas (>1 ha) and be more livestock-focused (i.e., own > 3 TLUs).

For Group 2 farms the observed trends are also complex (Section Household groupings and market access). Whilst farms in this group tend to be larger (>2 ha), far from markets, and according to model results they could benefit the most from improved market access (i.e., proximity to road), they do not show consistent dietary diversity scores. A theory put forward by Frelat et al. (2015) proposes that the more isolated a household is from markets, the more land it requires for producing food. In the case of these households however, and with the exception of households from Cluster 5 which is within a highland perennial farming system (Section Study sites), the dietary diversity is generally poor suggesting the larger areas cultivated are not ameliorating poor dietary diversity within an agropastoral or pastoral farming system (Section Study sites). That the ownership of generally large livestock holdings has also not ameliorated dietary diversity seems counter-intuitive, but does align with other findings from the literature suggesting that livestock holdings have diminishing returns (see Azzarri et al., 2015; Frelat et al., 2015). Across all clusters, our model finds that households with "Livestock Holdings" <4 TLUs and >5 TLUs are associated with lower HDDS (i.e., 4–5 TLU appears to be "optimum"). On the other hand, livestock diversity is, in general, positively linked to dietary diversity *via* the increased variety of animal products consumed, which is also in line with findings in the literature (Azzarri et al., 2015). Indeed, the much higher average diet diversity achieved by households in Cluster 5, which have much higher on-farm diversity provides further evidence for the importance of on-farm diversity when market access is difficult.

High on-farm diversity and good market access (i.e., proximity to road) are common among Group 3 households, which tend to have dietary diversity scores of around 5, and are all within a maize mixed farming system (Section Study sites). Using the evidence provided by Frelat et al. (2015) that 0.4 ha is enough to feed a household of 4.4 MAE, it appears that households in Group 3 produce enough food for consumption and for sale at market (household sizes tend to be <10 members and the areas cultivated are 1–3 ha). This chimes with Conelly and Chaiken (2000) who find that commercialization and diversification can go hand-in-hand *via* the implementation of intercropping farming methods, whereby subsistence crops suitable for human and animal consumption are grown alongside cash-crops such as coffee, tea, or French beans.

Across the 12 clusters, the mixed responses to market access variables, on-farm diversity, livestock holdings and land cultivated variables reflects the conflicting views found in the literature. Grouping clusters based on their characteristics and similitude of results highlights that location and resource availability are integral to understanding household strategy and provide a more nuanced interpretation.

Overall, our model results show neither specialization nor diversification to be a panacea. In the right context, each strategy has the potential to improve household dietary diversity. However, our model does provide some study-wide findings. Contrary to multiple studies, including the meta-analysis by Qaim et al. (2016), we find that consistently across all 12 clusters a change in household income has limited influence on the odds of a unit change in HDDS. The low influence of income on household dietary diversity is consistent with findings in other studies (e.g., International Food and Policy Research Institute, 2013; Kadiyala et al., 2014; Castello et al., 2015). Furthermore, the fact that our model also finds the number of household members to be statistically insignificant in determining dietary diversity is not outside the literature. The number of household members is an important source of on-farm labor, but household dietary diversity and household size tend to be negatively correlated (Abafita et al., 2016). Household members can generate off-farm and non-farm income based on their assessment of marginal return (Stifel and Minten, 2008), but the effect this income has on nutrition differs depending on its source (Barrett et al., 2001). Income from the sale of farm produce has limited effect on diet diversity (Wiggins and Keats, 2013; Kadiyala et al., 2014). Conversely the sale of household members' labor or the accruing of remittances correlate with an improved HDDS, particularly if financial control is with a female household head (Castello et al., 2015; Koppmair et al., 2017).

The potential of spatially explicit multi-level models

Qualitative studies (e.g., Wiggins and Keats, 2013) can provide rich information important to deciphering the use of markets and the effects of market access on nutrition at the household level. Unfortunately, the numerous factors households consider when formulating their livelihood strategy means that qualitative studies cannot provide representative guidance on all agriculture-nutrition pathways. Conversely, large quantitative studies (e.g., Qaim et al., 2016), use surveys of multiple thousands of households to perform global statistical analyses returning parameter estimates for the most effective drivers of household nutrition. Unfortunately, these studies are unsympathetic to local variations, as they tend to address only entire study areas, and can suffer from an "ecological fallacy", whereby correlations and parameter estimates at the global level do not represent the various experiences at the local level (Subramanian et al., 2009). There is, therefore, a need to apply methods that inherently take account of local context, whilst not losing the statistical power provided by large data sets. In this sense, deciphering household strategies by place allows for a more nuanced interpretation of data sensitive to local contexts (Fotheringham, 1997), with the results possible to be used to formulate locally specific interventions.

There is growing recognition that efforts to improve the nutrition and food security of the rural poor need to consider agricultural production, food purchases, food culture, gender empowerment, and geographical context, as best exemplified by the burgeoning narratives around the "food system" (Fanzo et al., 2020; Stefanovic et al., 2020). However, the development of a monitoring framework for all of these factors is in the early stages (Fanzo et al., 2021), and implementation currently lags behind aspiration. The multi-level model proposed here provides a way to account for many of these issues, which can be place-specific (e.g., relating to climate and market infrastructure), and simultaneously assess the impacts due to farm household-level changes within specific locations. This analytical method goes beyond what is possible with meta-analysis, and allows for the spatial disaggregation of policy-relevant insights.

Specifically, our finding that household proximity to roads was far more important than proximity to a physical marketplace, has major implications for infrastructure development planning. We also found that for households already close to roads ($<$10 min) a combination of diverse crops for home consumption with one or two high value products (often livestock) was the most successful strategy to achieve dietary diversity. For households further from roads, farms tended to be larger and with more livestock, but with lower dietary diversity. Livestock ownership $>$5 TLU (in cattle mass equivalent) was associated with declining dietary diversity scores. In such contexts if the construction of roads is prohibitively expensive, then policy interventions to support more nutritious diets could focus on outreach to these harder-to-access areas, with a focus on improved crop diversity for home consumption.

Study limitations

Some of the elements of the adopted methodology entail some degree of uncertainty as explained below. Spatially varying regression models, such as those used in this study, inherently rely on a small number of data points at each "place". Techniques to "pool" or "borrow" data with similar traits from across the dataset do increase statistical power, but outliers can have a disproportional impact. Whilst efforts were made to identify and remove such outliers, the risk remains. Furthermore, the market access variables used in this study entail some broad assumptions about the transport mode and its speed (i.e., walking when off road, using car/van when on road). However, a more fundamental weakness in the use of travel time to urban marketplace as an indicator of market access is the role of agricultural traders operating from their own vehicles. As Nandi et al. (2021) note, there is no consensus within the literature as to when the proximity to road or the travel time to physical market place is a more useful indicator. A further source of potential uncertainty is the dietary diversity recall reported by survey respondents. The use of lean season and flush season as recall periods means that the period of recall can be as much as 11 months in the past. This is contrary to best practice guidance Verger et al. (2019) suggesting the use of recall period the 24 h previous to the survey. Interviewee memory of food consumption 11 months in the past is likely to include some inaccuracy, but it does allow the recall periods to be compared regardless of the timing of the survey.

Conclusion

The risk of malnutrition, particularly micro-nutrient deficiency, is high among smallholder farmers in Sub-Saharan Africa, including Kenya. It is widely accepted that the existence of markets can play a key role for achieving good nutrition levels at the food shed level. In this study we used two proxy measures of market access and six household characteristics extracted from almost one thousand household surveys in South and West Kenya, to conduct a spatially-explicit, multi-level assessment of the impact of market access on household dietary diversity. Our analysis identified 12 clusters and 3 more general groups of households involving different configurations of farms and market access, each of which has been supported by studies conducted elsewhere. This indicates that the spatially explicit approach used in this study indeed permitted the identification of meaningful nuances within the study population. When looking critically at the model results it could be proposed that there is an optimum market access to land cultivated ratio to achieve dietary diversity. This optimum is for households whose market access is between 3 and 10 min walking distance to the nearest road, cultivate land between 1 and 2 ha and own livestock holdings between 4 and 5 TLUs. But this belies that across the 12 household clusters identified, the households have very different available resource and implement very different dietary diversity strategies. With the increasing threat of climate change and population pressure on smallholder farmers, the imperative for designing locally effective interventions to increase food security that are based on locally-specific evidence has never been higher. The methodology proposed here provides a way to simultaneously assess the varying impacts of multiple variables at the farm-household level at specific locations. This analytical method goes beyond what is possible with meta-analysis, and can permit policy-relevant insights to be spatially disaggregated.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://doi.org/10.7910/DVN/9M6EHS.

Author contributions

DM: overall author responsible for all parts of the research. LW: detailed guidance on modeling and model development. JH and MW: study concept, data, and text development. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Publisher's note

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