Agricultural Systems 224 (2025) 104250

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

A farm typology development cycle: From empirical development through validation, to large-scale organisational deployment

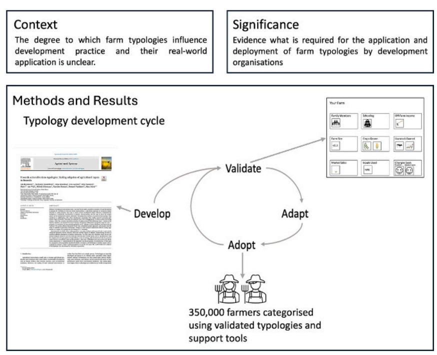
Rhys Manners [a,*], Jim Hammond [b], David Renaud Umugabe [c], Milindi Sibomana [c], Marc Schut [d]

[a] International Institute of Tropical Agriculture, Kigali, Rwanda
[b] International Livestock Research Institute, Nairobi, Kenya
[c] One Acre Fund, Kigali, Rwanda
[d] CGIAR System Organization, Nairobi, Kenya

HIGHLIGHTS

- Farm typology utility for, and deployment by, development actors is understudied.
- Iterative validation and adaptation needed for real-world typology application.
- Moderate-high agreement between farmers', extensionists', and empirical typologies.
- Development actor categorised 350,000 farmers, supporting tailoring of interventions.
- Quicker methods for typology validation are needed for dynamic farmer circumstances

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Leonard Rusinamhodzi

Keywords:
Farmer typologies
Validation
Deployment
Adoption

ABSTRACT

CONTEXT: The publication of farm (or farmer) typologies has increased over recent years. The purpose of these studies is usually to differentiate groups of farmers so that they are "targeted" with specific agricultural innovations, or best-bet interventions can be "prioritised". The degree to which such typologies actually influence development practice is however unclear, and little has been published on that topic.

OBJECTIVE: The paper aims to move narratives and practices around farm typologies from theoretical to applied and present a novel methodology for typology validation. We worked with a large-scale development organisation to develop a typology for their use, and report here on the process of enabling the organisation to make use of the typology. The lessons from this process are intended to inform the use of farm typologies in agricultural development work.

METHODS: A typology of farming households was derived from a household survey in Rwanda (previously published), in partnership with a large-scale agricultural development organisation. Responding to the organisation's requests, the researchers created a decision tree tool to rapidly assign households to types; conducted validation exercises to establish confidence in the typology and the decision tree (making adaptations as needed). Validation was with farmers and extensionists and included developing key word and pictorial representations of farm types which were compared against the empirical typology. The decision tree was tested and questions

* Corresponding author at: KG567 #7, Kigali, Rwanda.
E-mail address: r.manners@cgiar.org (R. Manners).

https://doi.org/10.1016/j.agsy.2024.104250
Received 25 March 2024; Received in revised form 19 December 2024; Accepted 19 December 2024
Available online 24 December 2024
0308-521X/

adapted to maximise accuracy. The organisation then used the tools for a period of two years. Finally, the researchers interviewed representatives of the organisation to find out how the tools had been used.
RESULTS AND CONCLUSIONS: The typology validation exercises showed a high level of agreement between farmers and extensionists, and a moderate level of agreement between the empirical typology and the types defined by farmers and extensionists. There was a low level of agreement in the Western province of Rwanda, where the socio-economic situation was radically different to other areas, which had not been accounted for in the empirical typology definition. Establishing the correct questions in the decision tree tool proved important. The organisation reduced the number of farm types, and categorised over 350,000 households, with four use cases developed for the farm typologies: planning for the recruitment of clients (farming households are referred to as clients by the organisation), client needs assessment, intervention adoption rate assessment, and monitoring of farmers along the organisation's conception of their (farmers') journey to prosperity.
SIGNIFICANCE: This study provides lessons on what is required for the application of farm typologies by development organisations.

1. Introduction

African smallholder farming households face an array of challenges (e.g. crop failures, pest and diseases, droughts and floods, and economic shocks). The opportunities for households to respond vary dramatically depending upon livelihood strategies and inherent capacities for change (e.g. Connolly-Boutin and Smit, 2016). Responses can be supported and strengthened by external interventions and innovations from public and private entities (CGIAR, 2024). Unfortunately, such interventions and innovations have not achieved their expected outcomes (e.g. Giller et al., 2011). Their limited benefits may stem from inadequate consideration of the diverse circumstances facing households, their dynamism responding to stressors creating moving targets, and their capacities to adapt (Bidogeza et al., 2009; Giller et al., 2011; Cortez-Arriola et al., 2015). For agricultural innovations to be relevant and enabling, characterisation of the multi-dimensional diversity of farms is necessary (Ruben and Pender, 2004; Descheemaeker et al., 2019). Consequently, it is expected that consideration of this diversity should improve targeting of specific demographic groups, prioritisation of appropriate interventions, and lead to higher rates of adoption (Tittonell et al., 2010; Lopez-Ridaura et al., 2018).

Farm typologies present an established and systematic approach to understand household diversity and can form the first step of generating tailored and adopted interventions (e.g. Landais, 1998; Giller et al., 2011; Cortez-Arriola et al., 2015; Chopin et al., 2015; Kuivanen et al., 2016). Typologies cluster farms using key structural, functional, or performance variables, and may be derived from multivariate statistical analysis (e.g. Cortez-Arriola et al., 2015; Douxchamps et al., 2016), expert knowledge (Madry et al., 2013), or a combination of the two (e.g. Pacini et al., 2014; Alvarez et al., 2018: Berre et al., 2019). The creation of typologies has undoubtedly improved understanding of farm diversity and (to a lesser extent) generated decision support tools for improved targeting of interventions (e.g. Alvarez et al., 2018; Hammond et al., 2020). Yet, despite the expected benefits of the insights generated from typology development, limited evidence is available that documents the pathway from development to real-world application.

Although widespread, typologies and their derivative tools may be left un(*der*)utilised. The reasons for this may include a lack of understanding of what they represent, no clear demonstration of the value added, a lack involvement with implementing partners in their development and continuous improvement/refinement, or typologies being unrecognisable to local stakeholders (Moreno-Pérez et al., 2011). This underutilisation may explain the limited evidence of typologies moving from academic papers (676 indexed on www.sciencedirect.com for 2023 alone) to real-world utility in supporting farmers. As LaFevor (2022) highlights, despite the increased focus on targeting and policy relevance, few studies demonstrate how typologies have been used for the basis of targeting (see Kaur et al., 2021 for an example of post-hoc typology analysis).

In this paper we contribute to the topic of *application* of farm typologies to enable greater development impact. We describe the process of working with a large-scale agricultural development organisation to develop, validate, and adopt a farm typology-based analysis and decision support tool to support programmatic decision-making. We build on previously published work (Hammond et al., 2020) in which 10 farm types were developed describing the farming, livelihood, and technology adoption characteristics of smallholder farmers in Rwanda. Working with the same development organisation, we assessed their needs and supported a process of validation, adaptation, which eventually led to adoption, although not quite as had been originally planned (see Fig. 1).

The work sought to continue the research cycle described in Hammond et al. (2020), with the validation and adaptation exercises continuing in 2019–2020, and adoption in 2021. We aimed to: i) validate the empirically derived typologies of Hammond et al. (2020), comparing validation methods; ii) assess the validity and report on the use of a decision support tool built from the typologies; and iii) reflect on the needs of an implementing organisation when using empirically derived typologies and the decision tree, drawing implications for typology development methods.

2. Methods

2.1. Description of the empirical typology

Hammond et al. (2020) generated a suite of farm typologies to describe the diversity of farming households in Rwanda. The aim of these typologies was to support the scaling strategy of a large-scale implementing rural development organisation in the region. In late 2018, ~2750 farming households were interviewed using the RHoMIS surveying tool (Hammond et al., 2017). Through the application of a minimum variable approach, key variables were identified for differentiating farming households, with cluster analysis used to generate the ten typologies. The key variables used for typology development were whether or not they grew maize and beans; livestock ownership measured in Tropical Livestock Units (TLUs), the land area cultivated in the last year, whether the household head was married or single, whether the household head had formal education, and the count of perceived positive changes which had occurred within the farm-household within the last four years (such as increased incomes, increased crop production, labour saving technologies used, etc.).

Following consultation with the development organisation, six farm

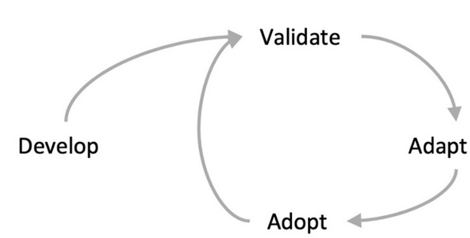


Fig. 1. Workflow of typology generation.

types were shortlisted as being of particular interest (Table 1). These were selected based upon whether: farmers could benefit from the product- and extension-based interventions of the organisation; the farm types were under-represented in the organisation's client list; and that they cover the widest perceived diversity of farms. The shortlisted farm types represented around 60 % of surveyed farms.

A decision support tool based on these typologies was also described (Hammond et al., 2020). The aim of which was to enable the rapid assignment of farmers to a given typology. This was done via a decision-tree model, shown in Fig. 2. Based on responses to a maximum of four yes/no questions, interviewees were assigned to one of the six prioritised farm types, with an accuracy of 79 % (Hammond et al., 2020).

2.2. Typology validation approaches

Validation of the typologies and decision-support tool in field conditions was identified as a prerequisite before the development organisation could consider them for wider use. Although typology validation is not nearly as commonly published as typology generation, previous studies have outlined methods for participatory approaches, which we considered appropriate to this context (e.g. Kuivanen et al., 2016; Alvarez et al., 2018; Thar et al., 2021; Sinha et al., 2022). We combined three approaches to validate the shortlisted typologies (Fig. 3): understanding the variables used by stakeholder groups to distinguish farm types, generation of farm types using icon-based variables, and comparing generated typologies with the empirically derived typologies from Hammond et al. (2020).

2.2.1. Selection of participants

We engaged two groups of stakeholders: farmers who had been interviewed in the original survey and local agricultural experts. The experts were themselves local farmers who also act as agricultural extension officers of the organisation. These extension officers facilitate interactions with other farmers, provide training on interventions and management practices, and offer general support to local clients of the organisation.

Farmers were selected through purposive sampling of the original survey (2713 households). Criteria for selection included: that households were distributed as evenly as possible across the 3 provinces (where data were originally collected) and that households were clustered in one or two districts per province, to ensure efficiency of sampling.

2.2.2. Data collection schedule

2.2.2.1. Farmers: Face-to-face interviews. Interviews were performed (ideally) with the same respondent as in the original survey (usually the household head). If the respondent was unavailable, an available adult confident to speak on all farm and household matters was interviewed. Each interview lasted a maximum of three hours. In total, 81 households were interviewed during the period August–September 2019 (Fig. 3). After review, only 77 of the interviews were rich enough to be analysed.

2.2.2.2. Farmers: Phone-based interviews. We identified a number of inconsistencies between farmers' responses in the original survey compared to the face-to-face interviews, for questions which responses were not anticipated to change greatly (educational and marital status of household head). We found that translations from English into Kinyarwanda had led to questions and response options which were ambiguous and culturally insensitive, particularly regarding definitions of an individual whose marital status is defined as single. We therefore developed a 20-min follow-up survey conducted by phone to correct these issues. In total, 82 farms were interviewed by phone in June 2020. Of these, we re-interviewed 14 of those face-to-face due to ongoing inconsistencies of responses (Table 2).

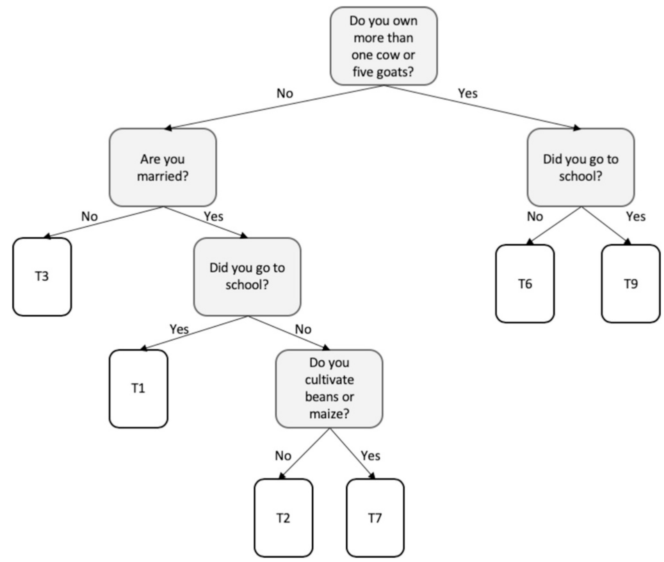


Fig. 2. Decision-tree model for clustering farms.

2.2.2.3. Local agricultural experts: Focus group discussions. Interactions with local agricultural experts were via focus group discussions (FGD), allowing for a more interactive and consensus-based approach to the validation. Three FGDs were performed in February 2020, with one performed in the Eastern, Southern, and Western provinces of Rwanda. Seven local agricultural experts participated in each FGD. The discussions lasted less than 3 h and were moderated by a representative of the development partner.

Despite the interaction type being different to that of farmers, the methods followed in the interviews of FGDs was the same. Unless stated otherwise, the deployed method was identical for farmers in the interviews or with local agricultural experts in the FGDs.

2.2.3. Local-knowledge farm typology: Verbal approach

Following a brief introduction, participants were asked to think about farms in their locality and the characteristics they would use to group them. Participants were invited to answer open-ended questions regarding how they described farms; how these farms differed; the drivers that differentiate farming types; and the characteristics they use

Table 1
Shortlisted farm types from Hammond et al. (2020).

Farm Type	% of surveyed households	Grows maize, bush beans, and/or climbing beans (modal yes/no)	Heads of livestock (mean TLU)	Land area cultivated (mean ha)	% of Household heads married	% of household heads with formal education	Positive changes in last 4 years (mean count)
1	12	Yes	0.4	0.3	82	72	1.1
2	13	No	0.5	0.2	64	14	1.1
3	20	Yes	0.4	0.3	0	12	1.3
6	13	Yes	1.5	0.7	80	20	1.9
7	28	Yes	0.4	0.5	100	0	1.7
9	15	Yes	1.9	0.9	91	100	2.9

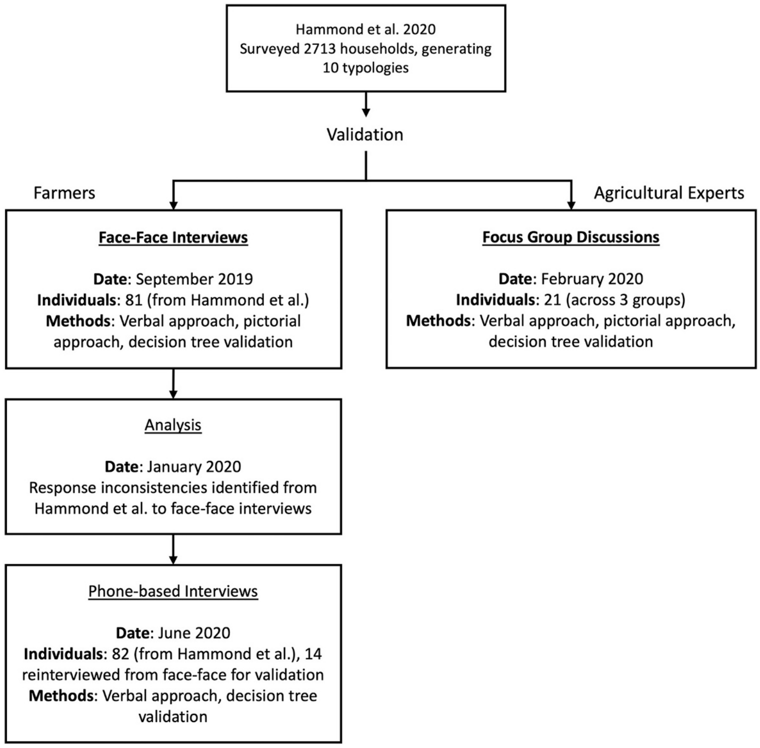


Fig. 3. Typology validation approach deployed.

Table 2
Distribution of interviewed farmers across farm types.

Farm Type	Face-to-Face Interviews	Phone-based Interviews	Face-to-Face and Phone-based Interviews
T1	12	7	3
T2	16	6	3
T3	25	13	3
T6	5	9	3
T7	13	28	1
T9	6	19	1
Total	77	82	14

to group farms in their area. During the interaction, an enumerator noted the key words and features, recording them in an Open Data Kit (ODK) form.

2.2.4. Local-knowledge farm typology: Pictorial approach

Following approaches described by Alvarez et al. (2018) and Lopez-Ridaura (personal communication), interviewees were invited to develop a pictorial representation of (simplified) farms, using icons ("pictograms") to describe various features. The features were selected to represent variables used in the empirically derived typologies. The farmers were asked to describe their own farms, and the local agricultural experts to develop typical farms in their locality.

Participants used a sorting technique, where they would look through a series of pictograms and identify the pictogram most relevant for them for each variable used in the empirical farm types (and other key features identified from that work): family size, education, off-farm income, farm size, crops grown, livestock owned, market sales, inputs sales, and farm changes. The method consisted of the following 4 steps (or 6 steps for the local experts):

Step 1: The interviewer described each of the variables and requested participants to consider the farm in question vis-a-vis the variables and pictograms presented, and to imagine how they could describe the farm using the pictograms provided (Fig. 4).

Step 2: The interviewer described a hypothetical typical farm in the region, expressly referring to the images provided: "Aimable lives in Huye, is married with two children (picks up the family pictogram), he completed primary school (picks up the rucksack pictogram). He currently farms 0.25ha (picks up <0.3ha card), grows mainly beans and maize (picks up maize and beans image), and has one cow and two chickens (picks up). He sells less than a quarter of his production at market. He uses NPK on his crops. He has seen 2 positive changes on the farm, with increases in income and market sales over the past 4 years."

Whilst describing this hypothetical farm, the interviewer placed the selected pictogram in each corresponding variable on the laminated paper for the farm description. Once completed the hypothetical farm was described using Aimable's characteristics (Fig. 5).

Step 3: After the interviewer characterised Aimable's farm, the interviewer went through the exercise again, explaining each of the pictograms' meanings and where to place them, whilst referencing the key for each variable (Table S1). The interviewer then asked the participant if they understood the exercise and if they had questions.

Step 4: Participants were invited to describe their own farm (or two typical farms in the area for the experts) using the pictograms. Following the description of the farm, the enumerator recorded the pictorial version farm into an ODK form. A photo was also taken of the finalised simplified farm.

Step 5 (Local Agricultural Experts only): Following completion, participants presented both farms they had generated. The facilitator sorted these into similar groupings, inviting participants to comment on whether the groupings were correct, and if not, where a farm should be placed. A single representative farm for each grouping was selected. Following grouping, the facilitator asked whether the diversity of farms in the area has been described. If participants believed any were missing, they were asked to describe them, with a pictogram-based farm created. Participants were then asked to estimate the approximate proportions of local farms represented by each of the developed farms.

Step 6 (Local Agricultural Experts only): Participants were presented, pictorially, with the empirical typologies (Hammond et al., 2020) and asked whether they existed in the area, whether they were similar to

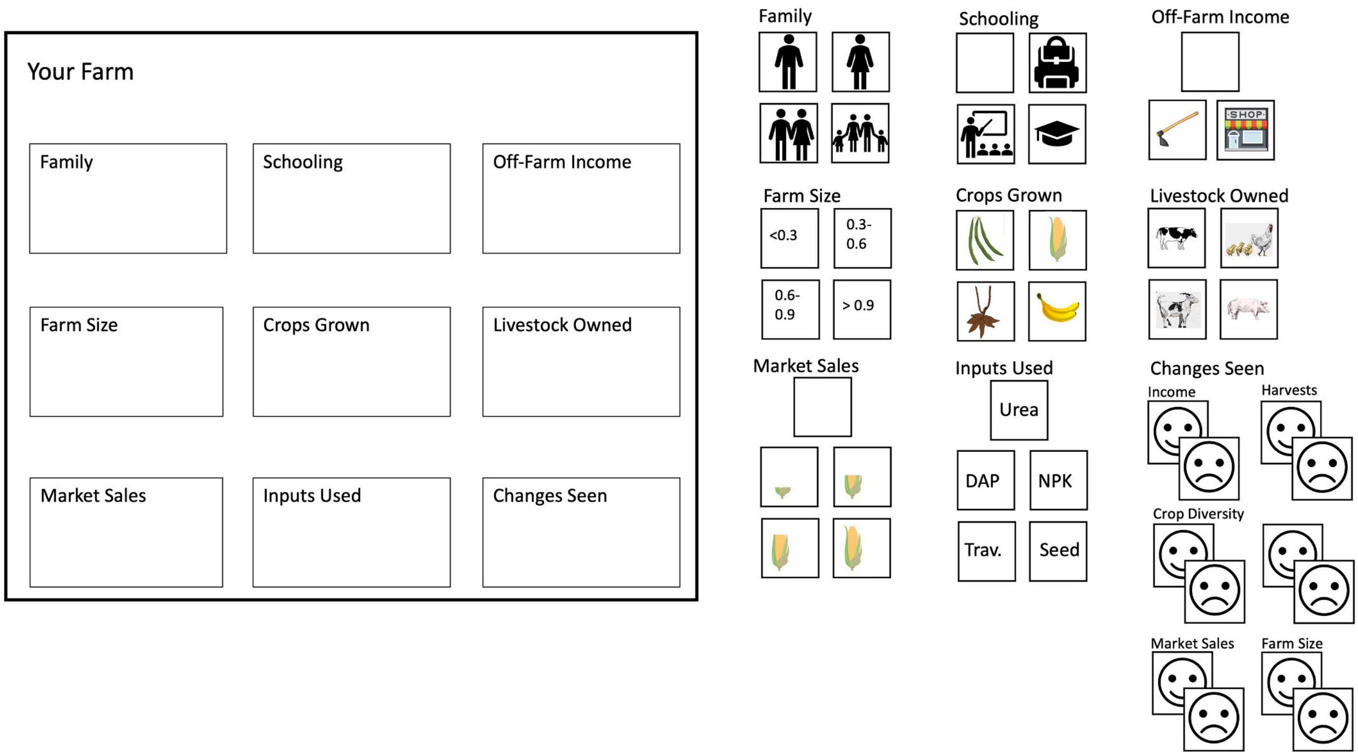


Fig. 4. Materials and their layout for interview.

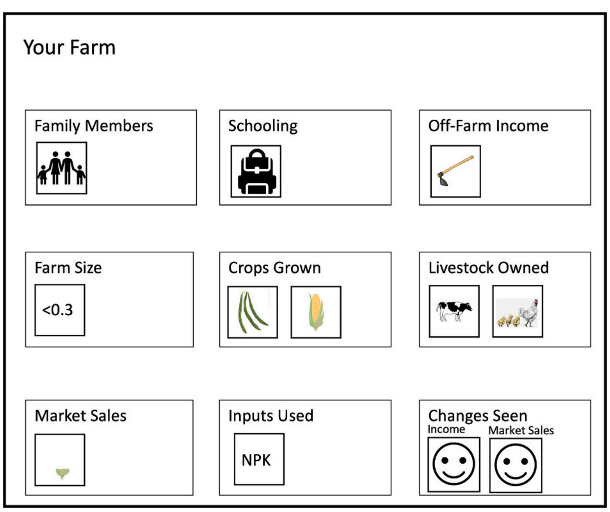


Fig. 5. Simplified pictorially represented farm.

those described in Step 5, and what could be added or changed to make the empirically-derived farm types more realistic and representative of farms in the region.

2.3. Comparing local-knowledge and empirical typologies

2.3.1. Comparison of variables derived from verbal descriptions

The key words taken from exchanges with farmers and local experts were compiled and sorted, grouping words representing similar concepts. The most common key word for a specific concept was retained, with a tally made for each. The key words were ranked on how frequently they were used. The farmers' choice of key words, the local experts' choice of key words, and the variables used for the empirically-derived typology were compared.

2.3.2. Comparison of farmers' pictorial descriptions of their own farms

The pictorial descriptions of farms were compared in two ways: against the empirically-derived typologies and the underlying survey data. First, the choice of each pictorial descriptor variable was compared against the corresponding variable recorded in the original household survey to check for response consistency. Second, the pictorial description was used to assign the farm to a typology class, and this was compared to the original typology found for the farm using the empirical method.

To convert the pictorial description to a farm typology class, we coded farmers' responses to each of the six variables (used in the empirical typology definition) to binary or simple vectors (Table S2). For example, the family question in which farmers selected the pictogram that best described their family (single male/female, couple without children, couple with children) was coded to married yes (1) and no (0)). For those variables which could not be converted to binaries, they were categorically coded. For example, the farm size was converted to: Below 0.3 ha (1), Between 0.3 and 0.6 ha (2), etc. From this, each farm was converted into a vector of six values (one for each variable). We did the same coding method for each of the empirical farm types to enable comparison. Each coded vector was then processed in the decision tree (Fig. 2) to generate a farm type for that pictorial depiction of the farm. We then compared each generated (pictorial) farm type with the farm type derived from the original household survey data.

2.3.3. Comparison of local agricultural experts' pictorial descriptions of farm types

Using the coding method described above, each of the experts' pictorial farm type descriptions was processed using the decision tree tool and assigned into one of the categories from the empirically-derived typology. This allowed comparison of the presence of different farm types in the different study sites as reported by the experts and by the empirical method based on the survey data. We also compared the prevalence for each farm type as estimated by the local experts compared to those found from the original survey analysis.

2.4. Validation of the decision tree

We also tested the validity of the decision tree presented in Hammond et al. (2020). Using the same sample of farmers described above, the decision tree questions were put to them, with a typology class assigned in function of these responses. This classification was compared to the empirically-defined typology. We performed the validation in two stages: via face-face interviews; and then later a phone call follow-up.

2.4.1. Face-to-face

During the face-to-face interviews with the farmers, the interviewer requested they think about their farm and respond to four questions (derived from four key variables used in the decision-tree in Fig. 2): i) 'Do you own more than one cow or five goats?'; ii) 'Are you married?'; iii) 'Did the household head receive a formal education?'; and iv) 'Do you cultivate beans or maize?' Binary responses were invited and recorded in a yes/no format in an ODK form. The questions were asked in Kinyarwanda.

2.4.2. Phone-based

Following analysis of the face-to-face interviews, we observed that responses to two key questions (educational and marital status) differed markedly from the responses recorded in the original survey. We therefore reviewed how these questions were posed in both interactions and discussed with colleagues fluent in both English and Kinyarwanda and Rwandan culture. We found inconsistency in question framing (from the original survey to the validation) in the translation from English to Kinyarwanda for the decision tree tool, and social ambiguity in response options. Following interactions with the development partner and taking advice from those with local knowledge, we considered that this may have accounted for the discrepancies. We revised the decision tree questionnaire translation (Table S3), developed responses which could only be interpreted in a binary manner, and conducted a phone-based follow-up with the same respondents to gather unambiguous response data on the questions regarding educational and marital status.

2.5. Adaptation and use of the typology and decision tree

Following the validation exercises, discussions were held with the implementing organisation to enable them to assess the validity of the empirically derived typology and the decision tree tool for their purposes. This involved explaining the methodologies, presenting results, and discussing the implications. It involved multiple interactions over time and between multiple individuals, mainly during 2020. Within the development organisation, results were discussed internally, and then further queries made to the research team. After the tools were considered to be acceptable to the development organisation interactions with the researchers decreased, down to about once every six months during 2021 to 2023. Over this period the development organisation made use of the typology and the decision tree, aligned to their needs, organisational strategy, and the evolving context. During preparation of this manuscript meetings were held to understand how the development organisation made use of the tools, and the findings are reported below in the results section.

3. Results

3.1. Typology validation

3.1.1. Farm description – Verbal approach

From the farmer and expert interviews, we tallied and ranked the most frequently used terms to differentiate farm types and compared those to the variables used in the empirical typologies (Table 4). Both farmers and local experts quoted farm size as the most important distinguishing characteristic for farms. Three of the six variables used in the empirical typologies were mentioned by farmers (farm size, livestock ownership, and crops grown). The most important variables used by farmers to differentiate farm types were farm size, farm productivity, livestock ownership, and (inorganic) fertiliser use. For local experts: farm size, soil fertility, crop management, farm productivity, and farm topography. Expert respondents used only physical and agronomic variables for distinguishing farm types, they did not use socio-economic variables. The farmer respondents considered household wealth and use of hired labour as less important distinguishing variables.

Table 4
Variables used to differentiate farm types.

Variable	Empirical Typology	Farmer Mentions (count (rank))	Local Agricultural Expert Mentions (count (rank))
Livestock ownership	X	17 (3)	
Farm Size	X	41 (1)	4 (1)
Marital Status (hh head)	X		
Formal Education (hh head)	X		
Crops Grown	X	8 (6)	1 (8)
Farm Changes	X		
Farm Productivity		20 (2)	3 (4)
Fertiliser (inorganic) Use		13 (4)	2 (6)
Hired Labour		10 (5)	
Wealth Status		3 (7)	
Soil Fertility			4 (1)
Crop Management			4 (1)
Topography			3 (4)
Land Ownership			2 (6)

3.1.2. Farm description – Pictorial approach

The findings from the pictorial approach are presented separately for farmer respondents and local agricultural expert respondents.

3.1.2.1. Farmers. Respondents' pictorial representations of their own farms were compared with the empirically-derived typologies for their farms. Fig. 6 shows the number of variables where the pictorial representation aligned with the empirical. 47 % of farms matched four or more of the six variables used in Hammond et al. (2020), and 87 % matched three or more variables. Only one farm matched all six variables.

Table 5 presents the discrepancy rates for the specific variables between the pictorial and empirical typologies. The variables with greatest discrepancy were the number of positive changes in farm and livelihood productivity changes (68 %) and land size (65 %). The level of disagreement (not-matching) between the empirical and pictorial typologies on farm size was surprisingly high. Positive changes are an abstract and dynamic variable, which may be open to misinterpretation. High discrepancy in farm size may be accounted for by farm types having very similar farm sizes. Empirical farm types 1–3 have average cultivated areas of between 0.2 and 0.3 ha, with 6 and 7 between 0.6 and 0.9 ha, and farm type 9 having greater 0.9 ha. Also farm sizes are highly dynamic with plots rented or leased between seasons. Such small differences could shift farms into different groups, especially if farmers have taken on more land, did not consider certain plots in the original survey, or were simply unsure of the definition of land size. That education and marital status had such high discrepancies in responses was confusing, these variables would be expected to have limited dynamism in such a short intervening period (<18 months).

Table 6 gives an overview of the consistency or agreement between how farmers self-categorised, using the pictograms, and their empirical farm type. The results show that only 30 % share a pictorial vision of their farm that matches their assigned empirical farm type. Agreement was especially low for farm types 1 and 2, which had 20 % and 0 %

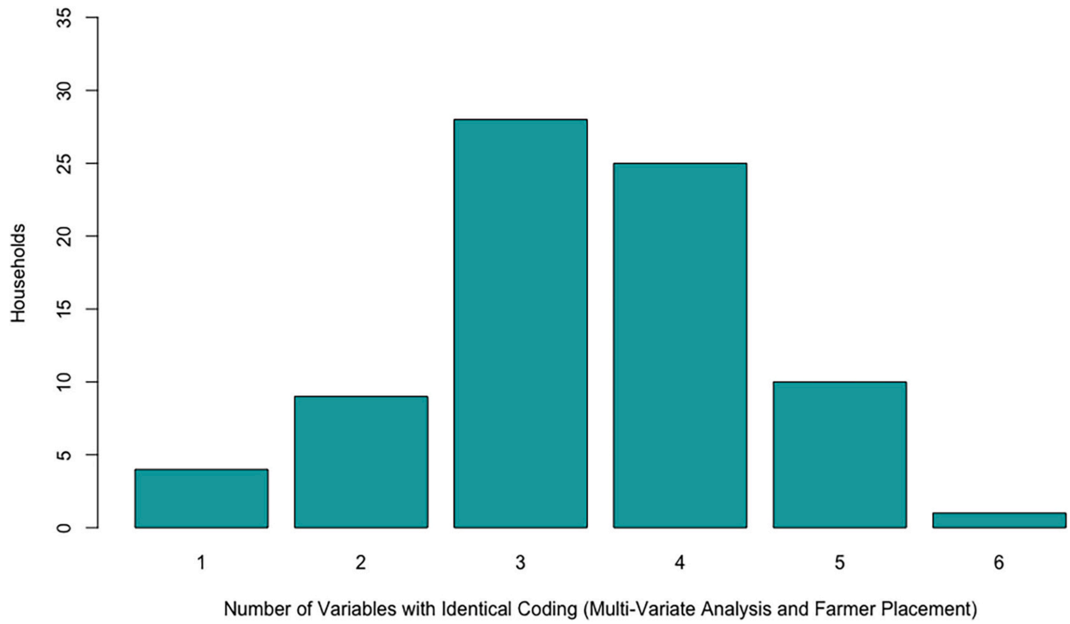


Fig. 6. Matching variables from pictograms and clusters across households.

Table 5
Discrepancies between coded households and coded clusters.

	TLU Ownership	Education	Marriage Status	Cultivation of Beans or Maize	No. of Positive Changes	Farm Size
Matching	56 (72 %)	42 (54 %)	53 (69 %)	60 (78 %)	24 (32 %)	27 (35 %)
Not-matching	21 (28 %)	35 (46 %)	24 (31 %)	17 (22 %)	50* (68 %)	50 (65 %)

* Three households didn't provide answer to this variable.

Table 6
Agreement between farmer self-categorise farm type and empirical farm type.

Empirical Farm Type	Farmers interviewed	Empirical Categorisation - Household Self-Categorisation Agreement	Empirical Categorisation - Household Self-Categorisation Agreement (%)	Empirical Categorisation - Household Self-Categorisation Disagreement	Empirical Categorisation - Household Self-Categorisation Disagreement (%)
T1	12	2	17	10	83
T2	16	0	0	16	100
T3	25	10	40	15	60
T6	5	2	40	3	60
T7	13	4	31	9	69
T9	6	5	83	1	17

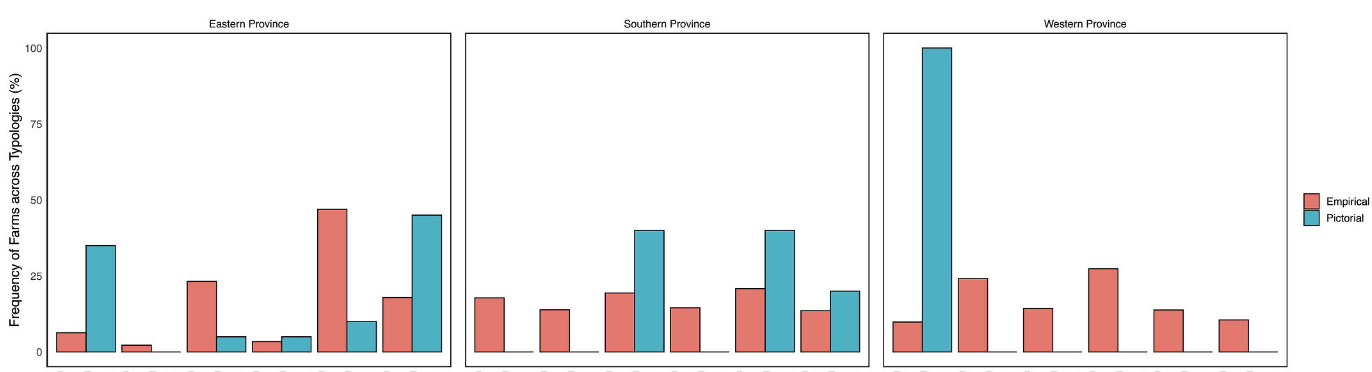


Fig. 7. Frequency of farms across empirical and pictorial typologies.

agreement. In the case of farm type 2, there was no self-categorisation to that type. In contrast, respondents in farm types 3–9 agreed with their empirical farm type at least 44 % of the time, with farmers in farm type 9 agreeing to the greatest extent.

3.1.2.2. Local agricultural experts. Thirty-four pictorial descriptions of typical farms were developed across three focus group sessions. The pictorial variables were input into the decision tree to assign each to one of the types identified in the empirical study. A pictorial example of each different farm type identified in each region is available in Table S4. In the Eastern Province, participants described 5 of the 6 shortlisted farm types. Each farm type was identified at least twice, with types 1 and 3 described four times. In the Southern Province four of the six shortlisted types were identified, with type 9 classified the most frequently. In the Western Province all farms developed were classified as type 1.

The local agricultural experts estimated the prevalence of the defined farms (Fig. 7). They estimated farm type 9 was the most common in the Eastern Province (41 %), type 3 in the Southern Province (38 %), and type 1 in the Western Province (100 %). This contradicts the empirical distribution, where farm type 7 was the most common in the Eastern (47 %) and Southern (21 %) provinces, and farm type 6 in the Western (27 %). The empirical analysis put farm type 9 (18 %) as the third most common farm in the Eastern province; farm type 3 was the second most common (19 %) in the South, and farm type 1 as the least common in the Western province (10 %). Local experts did not depict farm type 2 in any region, and infrequently represented farm type 6. This is particularly interesting in the Western Province, where these two farm types were suggested to be the two most common by the empirical analysis.

3.1.3. Expert response to the empirical typologies

The local expert participants were presented with the empirical farm types. In general, the feedback was positive, in the Eastern and Southern provinces, participants agreed that all empirical farm types were present in the region. They also stated that, in general, the empirical farm types were similar to what had been developed pictorially, even if the frequency estimates were different. In the Western Province, participants stated that that local farms from their experience diverged greatly from those portrayed in the empirical typologies, this is evidenced in Fig. 7.

3.2. Validation of decision tree

In the original testing of the decision tree, using the 2018 survey dataset, it successfully categorised 79 % of households to the correct farm type (Table 8). Using the coded pictorial descriptions of farms from the data collected from the face-to-face farmer interviews, the success rate dropped to 30 % (Table 6). The decision tree struggled in classifying farm types 1, 2, 6, 7. The authors suspected the reduction in accurate classification was primarily due to changes in how respondents reported their educational and marital status. Changed educational status of household head was reported by 39 % of cases and marital status change reported by 58 %, compared to the original data 2018 survey. Fourteen of the 77 individuals in the face-to-face farmer interviews responded almost entirely differently to their answers to these and the other key variable questions from Hammond et al. (2020).

An updated questionnaire was designed with improved phrasing and use of Kinyarwanda to gather unambiguous responses from the farmer respondents (see Methods section 2.5). The revised questions (and translations, Table S3) improved the response consistency, from 53 % to 88 % for marital status and from 42 % to 94 % for educational status. Using these updated responses, we retested the adapted decision tree and found its accuracy increased to 60 %, a considerable improvement, but still below the 79 % of the trained data from the baseline (Table 8).

Table 8
Outputs of decision tree across different data sets.

Farm Type	Baseline (untrained sample $n = 1560$)		Face-Face Interviews ($n = 77$)		Farmers from Face-Face Interviews in Phone-based interview ($n = 14$)		Farmers from Validation in Phone Follow Up. Using Validation and Updated Questions ($n = 14$)		Phone Follow Up Baseline and Updated Questions ($n = 82$)	
	Decision tree categorisation (households)	Correctly Categorised (%)	Decision tree categorisation (households)	Correctly Categorised (%)	Decision tree categorisation (households)	Correctly Categorised (%)	Decision tree categorisation (households)	Correctly Categorised (%)	Decision tree categorisation (households)	Correctly Categorised (%)
T1	188	51	34	21	8	25	2	50	7	43
T2	195	18	0	0	0	0	0	0	6	0
T3	317	93	13	70	2	0	6	17	11	73
T6	181	80	4	25	1	0	3	0	9	56
T7	463	94	20	30	1	0	3	33	28	83
T9	216	100	6	50	2	0	0	0	19	74
Overall Accuracy of Decision Tree		79		33		14		22		60

3.3. Deployment of the decision tree

Following the testing and adaptation processes described, the development partner began to use the typologies and deploy the decision-tree in their activities. In March 2021, the decision-tree was embedded into the partner's data collection tools used by their field officers. During four agricultural seasons, 2021 A, 2021B, 2022 A, and 2022B (A refers to the growing season between September–January, B covering the period February–June) the decision tree was deployed, with almost 1 million responses collected (Table 9). Responses were collected from more than 350,000 individual clients of the organisation, covering ~40 % of the organisation's clients in Rwanda. Some farmers were categorised multiple times across the four seasons, accounting for the almost 1 million categorisations. Across the four seasons data was collected across all 30 of Rwanda's districts, extending beyond the 20 districts which were used for the original typology analysis and decision tree tool creation.

The distribution of farms across farm types during the data collection is inconsistent with that of Hammond et al. (2020). From the deployment of the decision tree, there appears to be a particular underrepresentation of type 2 (0.6–0.7 % of farmers), compared with 12 % in the original survey data. These results seem to confirm, or align more closely with the local agricultural experts, where no type 2 farms were generated. We note that farm type 2 farmers are categorised by small-scale cassava production, not a focus of the development organisation. For farm types 1, 6, and 9, they appear to be overrepresented in the data collected by the partner, compared with the original data, with farm types 3 and 7 are underrepresented. We note that in each data collection moment (season) most farmers were categorised into the 'wealthier' groups (6–9).

The timeline of collection of these distributions of farms is too short to generate any valid conclusions on the dynamism of farms with farm types, or the farm types themselves. Across the two years of collection and four seasons, the relative distribution appears stable.

4. Discussion

The key contributions of this article were to trial various participatory validation methods, for an empirical typology; and to reflect on how to improve the science-development interface whereby a development organisation makes use of a farm typology. Farm typologies are widely used in the academic literature (e.g. Huber et al., 2024), although there is less focus on their validation (e.g. Alvarez et al., 2018; Kumar et al., 2019), and negligible description of their application and utility in real-world situations. We discuss these two key contributions below.

4.1. Approaches to validation of empirically derived typologies

We deployed a novel combination of validation methods, collecting key terms which informants used to categorise farms, constructing pictorial typologies from icons representing specific aspects of farms, and by presenting the previously defined (empirical) typology for discussion. Informants were drawn from local farmer and from local expert (extensionist) pools. We followed an ex-post approach, engaging farmers and experts after the empirical typologies had been finalised (Burton and Wilson, 2006; Thar et al., 2021; Sinha et al., 2022). This allowed comparison between the informant farmers' self-description and their empirically-defined farm types.

One challenge thrown up in interpretation of the results was deciding which source most accurately described the real situation. Where findings between the informant groups and the empirical typology were well aligned, that could be interpreted as confirmation of "correctness". However, when the findings did not align it was not straightforward to decide which of the differing observations was "correct". For example, in the Eastern province, the local experts identified Farm Types 1 and 9 as the most common, but the empirical typology identified Types 3 and 7. Which is correct? Did the survey have a more unbiased perspective due to the quasi-random sampling over the entire province, and the local experts were biased for some reason, perhaps due to the localised geography of where they worked, or the particular types of farmers who made use of their extension services? It is hard to say without conducting further research.

Differences in knowledge and conceptualisation skills also came into play. For example, the local experts chose to use no demographic variables in their typology construction, the farmers used some simple demographic variables, and the researcher created some quite abstract variables based on past experiences over preceding years. It may not be a coincidence that when asked to construct pictorial typologies based on these abstract variables, farmers frequently did not describe themselves in the same way that the empirical typology had. However, farmers also commonly assigned themselves into different land size categories compared to what had been recorded in the original household survey. This is not surprising considering the dynamism of land size in farming communities of Rwanda, with owned and rented land cultivated interchangeably between seasons, based upon available resources. This raises questions about the accuracy of survey data and suggests that without physical measurement of land, self-reported land size data should be considered an estimate, subject to change. Georeferencing of farmer plots could address this problem, at a cost.

There are two lessons to be drawn from these observations. The first is to accept a degree of "fuzzyness" is probably unavoidable, acknowledging that the participatory validation can only be confirmatory, and the analyses unavoidably contains multiple sources of error - a well reported outcome of surveying (e.g. Wollburg et al., 2021). The key question of how much fuzzyness to accept (and on what issues) relates to the purpose of the typology – in this case it was to guide an organisation's decision making regarding the design and targeting of interventions for their client population. What was most important to the organisation was distinguishing farmers with different characteristics relating to the technologies and practices which the organisation promoted. The organisation was satisfied with an overall confirmation that the types identified existed and represented real differences in the population, even if there was little agreement about the prevalence of each type.

The second lesson relates to acknowledging the differences in conceptualisation between different stakeholders involved in typology

Table 9
Categorisation of farmers for farm types using the decision-tree.

Farm Type	Hammond et al., 2020 % Distribution	2021 A		2021B		2022 A		2022B	
		No.	%	No.	%	No.	%	No.	%
T1	12	43,058	20.7	34,794	20.1	57,323	20.5	46,047	20.1
T2	13	1374	0.7	1156	0.7	1676	0.6	2633	0.7
T3	20	25,475	12.2	21,471	12.4	34,371	12.3	43,940	12.7
T6	13	44,069	21.2	26,317	21.6	58,715	21.1	69,685	21.1
T7	28	33,024	15.9	26,317	15.2	43,606	15.6	57,088	15.3
T9	15	61,264	29.4	68,016	30.2	83,772	30.0	98,357	30.2
Total		208,264		173,518		279,463		229,067	

construction and validation; and leveraging those differences for maximum benefit. We propose a marginally adapted approach to the one we used, bearing some similarities to the approach proposed by Alvarez et al. (2018). Taking a more informant-centric approach, with multiple opportunities for feedback offers a more rounded understanding of the diversity of farming households, and strengthens the validity (Huber et al., 2024). We recommend informant input before creation of the typology and then present the typology back to informants for validation. The approach would be to:

1. First, conduct a typology scoping exercise with the development partner organisation to understand the general requirements. This could be done in an open conversational format, with the partner sketching out the ideal result they are hoping for, including potential discriminatory variables and the expected uses the typology would be put towards.
2. Second, conduct a typology construction exercise with farmers and/or local experts. This could first elicit key terms used to discriminate farm types and the different states of the key terms (e.g. if land size was a key term, what would the thresholds be to determine a small or big farm? Should there be a medium farm size category?). These key terms could be sketched as icons and common farm types described by the informants within the geographies in which they are familiar.
3. Third, the researchers should compile a long list of potential variables for empirical typology creation, based on the two above appraisals, farm typology theory, and their own hypotheses. A household survey should be carried out covering the geographies of interest. Empirical typology creation could follow any of the established approaches and could include more abstract or complex variables.
4. Fourth, to present the typologies (and prevalences) back to farmers and/or local experts for confirmatory validation. They could comment on the degree to which they recognise the types, the prevalence, and they could attempt to allocate case study (or their own) farms into the typology.
5. Fifth, to present the typology back to the development organisation and attempt to integrate it into their operational model.
6. Sixth, to repeat steps 1–5 at pre-determined temporal steps (e.g. every year, 5-years, or 10-years) based upon budget availability and programme requirements. This ensures that typologies remain relevant and representative of contemporary farm types.

4.2. Towards adoption of the typology by the development organisation

Two "products" were provided to the development organisation: the typology definitions and the decision tree to rapidly assign any respondent into one of the farm types. Uptake and use of these by the development organisation took a period of years and involved iterative communication between members of the research team and the development organisation, as well as iterative communication between actors at different levels and with different objectives within the development organisation. The first lesson to draw is that the serious uptake of a typology-based approach to guide development investment entails a substantial time commitment for all parties involved.

The ways in which the typology and decision tree were used evolved over a period of five years (2018–2023). The initial plan for the typology study was made and executed in 2018, and in 2019 the organisation made sense of the findings and requested the validation study. From 2020 to 2022 the organisation used the typology and decision tree in various ways and in 2023 they reflected upon it both internally and with the research team.

The initial purpose of the typology was to provide information on potential adoption rates of their products and identify opportunities for expansion of the development organisations' client base, both into new areas and into new population segments in already-served areas. Some useful insights were obtained, notably the under-representation of some of the poorest sector of the communities (a common challenge in agricultural development – see Hammond et al., 2023a; Barrett, 2005) in hindsight the demand for agricultural support was so high that the organisation scaled their activities over the entire country. In addition, the misrepresentation of farm types in the Western province could have led to poor investment decisions – highlighting the need for some validation exercises and the importance of developing context specific typologies. Despite this, the scaling approach adopted by the organisation has followed a blanket approach, with little optimisation of product offerings or training services to farmers, offering a continued entry point for typology derived insights.

The second use of the typology and decision tree was to design intervention packages for specific sub-groups of the population (types or combinations of types). The typologies were to be used for the intervention package design and the decision tree was used to rapidly classify clients so that specific packages could be recommended to them. This followed the logic of Descheemaeker et al. (2019) who outlined the benefits of designing relevant interventions for farming groups, which should lead to higher adoption rates (Tittonell et al., 2010). Here the decision tree tool was an essential component, allowing the classification at grass-roots level of clients within a few minutes. The first step of this was initiated in 2021 and continued in to 2022, with around 350,000 farmers (clients) categorised during the four growing seasons. After trialling the approach, the decision was taken not to limit the services offered according to farm type.

The third use was to gather information on the adoption rates of promoted interventions, evaluating which farm types adopted more (or less) heavily. These adoption rate studies were conducted for established products such as improved maize seed, fertilisers, or vegetable garden training; but were also conducted for pilot products (e.g. spray pumps, cookstoves, or mobile phones) in order to gather information to guide deployment decisions. Substantial variation in adoption rates was observed between types, which prompted the organisation to conduct qualitative research to better understand the needs of different farm types in relation to specific practices or technologies; then influencing design and delivery of interventions. A decision was taken to continue this adoption and needs assessment approach. Were comprehensive data available, this would offer a tantalising opportunity to test the hypothesis that tailoring interventions encourages adoption (e.g. Lopez-Ridaura et al., 2018).

The fourth use of the typology was conceptualised later (2022–23) and entailed using the typology to monitor change in the population served by the development organisation. One of the guiding principles of the organisation is their "farmer journey" by which client farmers are conceptualised to transition from hunger (low subsistence), to self-sufficiency, to advancement to prosperity (commercial). There are observable criteria associated with each step and the services of the development organisation are intended to enable progress along this trajectory. The idea was to align the farm types into these four categories and then to assess changes in the proportion of clients (or the general population) in each of the four categories. Alternatively, the progress of individual clients could be tracked over a period of years. However, the original farm types did not align well with the farmer journey, so this was not possible. Nevertheless, the development organisation set this as an objective for future typology work.

A few additional key points emerged from the reflection process conducted by the development organisation in 2023. First was that the approach of generating an empirically based, validated typology and then a tool for rapid allocation of clients into the typology was considered valuable. Second was that after five years, the typology was outdated, due to the rapidly evolving socio-economic situation, national policies, and the organisation's own evolving agenda and business model. This is well noted in the academic literature: Giller et al. (2011) described farms as moving targets, with typologies only relevant for a given moment (Kostrowicki, 1977), and needing to be continually updated (Valbuena et al., 2015; Landais, 1998; Shukla et al., 2019). The development organisation stated intention to revise the typology based on new data, and with the farm types better aligned to the organisational vision of the farmer journey. This suggests a need for more agile (see Hammond et al., 2023b), cost-effective, and rapid typology creation process than currently exists. This may involve more user-friendly methods of typology generation (e.g. Hassall et al., 2023) but must also involve greater understanding of the potential uses of the typology to design the most fit-for-purpose and actionable analysis.

5. Conclusions

In this study, we report on the process of co-developing farm typology analysis and decision support tools with a large-scale development organisation. We deployed a novel validation method for the farm typologies and supported the use of a decision tree tool to rapidly assign respondent farmers to farm types. The deployed validation methods entailed dynamic engagement with farmers and extensionists, and included developing key word and pictorial representations of farm types which were compared against the empirical typology. Moderate overlap was found between the results, leading to some adaptation of the typology and then uptake by the development organisation. The decision tree tool was tested and also adapted to maximise accuracy. The organisation then used the tools for a period of two years. Through this mixed methods approach, farm interventions were tailored to clients' needs, adoption rates studied, and evidence gathered for organisational decision making. This deployment saw 350,000 households categorised into the farm typologies, with four use cases defined by the development organisation. After five years the typologies were considered outdated, highlighting the need for typology methods to be more agile, enabling regular updates, ensuring continuous real-world utility if they are to be helpful for guiding development investment.

CRediT authorship contribution statement

Rhys Manners: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Jim Hammond:** Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **David Renaud Umugabe:** Writing – original draft, Investigation. **Milindi Sibomana:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Marc Schut:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Marc Schut reports financial support was provided by Belgian Directorate General for Development Cooperation and Humanitarian Aid. Rhys Manners reports financial support was provided by CGIAR. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank the farmers and local agricultural experts for their time and willingness to participate in this research. This work was supported by the Belgian Directorate General for Development Cooperation and Humanitarian Aid (DGD) through the Consortium for Improving Agricultural Livelihoods in Central Africa (CIALCA- www.cialca.org); and the CGIAR Initiatives for Digital Innovations and the Sustainable Intensification of Mixed Farming Systems.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2024.104250.

Data availability

Data will be made available on request.

References

Alvarez, S., Timler, C.J., Michalscheck, M., Paas, W., Descheemaeker, K., Tittonell, P., Andersson, J.A., Groot, J.C.J., 2018. Capturing farm diversity with hypothesis-based typologies: an innovative methodological framework for farming system typology development. PLoS One 13, e0194757. https://doi.org/10.1371/journal.pone.0194757.

Barrett, C.B., 2005. Rural poverty dynamics: development policy implications. Agric. Econ. 32, 45–60. https://doi.org/10.1111/j.0169-5150.2004.00013.x.

Berre, D., Baudron, F., Kassie, M., Craufurd, P., Lopez-Ridaura, S., 2019. Different ways to cut a cake : comparing expert-based and statistical typologies o target sustainable intensification technologies, a case study in southern Ethiopia. Exp. Agric. 55, 191–207. https://doi.org/10.1017/S0014479716000727.

Bidogeza, J.C., Berentsen, P.B.M., De Graaff, J., Oude Lansink, A.G.J.M., 2009. A typology of farm households for the Umutara Province in Rwanda. Food Sec. 1, 321–335. https://doi.org/10.1007/s12571-009-0029-8.

Burton, R., Wilson, G.A., 2006. Injecting social psychology theory into conceptualisations of agricultural agency: towards post-productivist farmer self-identity. J. Rural. Stud. 22, 95–115. https://doi.org/10.1016/j.jrurstud.2005.07.004.

CGIAR, 2024. New Results Dashboard. Available at: https://www.cgiar.org/food-security-impact/new-results-dashboard/. Last accessed: 25/03/24.

Chopin, P., Blazy, J.-M., Doré, T., 2015. A new method to assess farming system evolution at the landscape scale. Agron. Sustain. Dev. 35, 325–337. https://doi.org/10.1007/s13593-014-0250-5.

Connolly-Boutin, L., Smit, B., 2016. Climate change, food security, and livelihoods in sub-Saharan Africa. Reg. Environ. Chang. 16, 385–399. https://doi.org/10.1007/s10113-015-0761-x.

Cortez-Arriola, J., Rossing, W.A.H., Massiotti, R.D.A., Scholberg, J.M.S., Groot, J.C.J., Tittonell, P., 2015. Leverages for on-farm innovation from farm typologies? An illustration for family-based dairy farms in north-West Michoacán, Mexico. Agric. Syst. 135, 66–76. https://doi.org/10.1016/j.agsy.2014.12.005.

Descheemaeker, K., Ronner, E., Ollenburger, M., Franke, A.C., Klapwijk, C.J., Falconnier, G.N., Wichern, J., Giller, K.E., 2019. Which options fit best? Operationalizing the socio-ecological niche concept. Ex. Agric. 55, 169–190. https://doi.org/10.1017/S001447971600048X.

Douxchamps, S., Van Wijk, M.T., Silvestri, S., Moussa, A.S., Quiros, C., Ndour, N.Y.B., Buah, S., Somé, L., Herrero, M., Kristjanson, P., Ouedraogo, M., Thornton, P.K., Van Asten, P., Zougmoré, R., Rufino, M.C., 2016. Linking agricultural adaptation strategies, food security and vulnerability: evidence from West Africa. Reg. Environ. Chang. 16, 1305–1317. https://doi.org/10.1007/s10113-015-0838-6.

Giller, K.E., Tittonell, P., Rufino, M.C., Van Wijk, M.T., Zingore, S., Mapfumo, P., Adjei-Nsiah, S., Herrero, M., Chikowo, R., Corbeels, M., Rowe, E.C., Baijukya, F., Mwijage, A., Smith, J., Yeboah, E., Van Der Burg, W.J., Sanogo, O.M., Misiko, M., De Ridder, N., Karanja, S., Kaizzi, C., K'ungu, J., Mwale, M., Nwaga, D., Pacini, C., Vanlauwe, B., 2011. Communicating complexity: integrated assessment of trade-offs concerning soil fertility management within African farming systems to support innovation and development. Agric. Syst. 104, 191–203. https://doi.org/10.1016/j.agsy.2010.07.002.

Hammond, J., Fraval, S., van Etten, J., Suchini, J.G., Mercado, L., Pagella, T., Frelat, R., Lannerstad, M., Douxchamps, S., Teufel, N., Valbuena, D., van Wijk, M.T., 2017. The rural household multi-Indicator survey (RHoMIS) for rapid characterisation of households to inform climate smart agriculture interventions: description and applications in East Africa and Central America. Agric. Syst. 151, 225–233. https://doi.org/10.1016/j.agsy.2016.05.003.

Hammond, J., Rosenblum, N., Breseman, D., Gorman, L., Manners, R., Van Wijk, M.T., Sibomana, M., Remans, R., Vanlauwe, B., Schut, M., 2020. Towards actionable farm typologies: scaling adoption of agricultural inputs in Rwanda. Agric. Syst. 183, 102857. https://doi.org/10.1016/j.agsy.2020.102857.

Hammond, J., Pagella, T., Caulfield, M.E., Fraval, S., Teufel, N., Wichern, J., Kihoro, E., Herrero, M., Rosenstock, T.S., van Wijk, M.T., 2023a. Poverty dynamics and the determining factors among east African smallholder farmers. Agric. Syst. 206, 103611. https://doi.org/10.1016/j.agsy.2023.103611.

Hammond, J., Pagella, T., van Etten, J., Ghosh, A., van Wijkm, M., 2023b. Editorial: agile data-oriented research tools to support smallholder farm system transformation. Front. Sustain. Food Syst. 7, 1128513. https://doi.org/10.3389/fsufs.2023.1128513.

Hassall, K.L., Baudron, F., MacLaren, C., Cairns, J.E., Ndhlela, T., McGrath, S.P., Nyagumbo, I., Haefele, S.M., 2023. Construction of a generalised farm typology to aid selection, targeting and scaling of onfarm research. Comput. Electron. Agric. 212, 108074. https://doi.org/10.1016/j.compag.2023.108074.

Huber, R., Bartkowski, B., Brown, C., El Benni, N., Feil, J.-H., Grohmann, P., Joormann, I., Leonhardt, H., Mitter, H., Müller, B., 2024. Farm typologies for understanding farm systems and improving agricultural policy. Agric. Syst. 213, 103800. https://doi.org/10.1016/j.agsy.2023.103800.

Kaur, J., Prusty, A.K., Ravisankar, N., Panwar, A.S., Shamim, M., Walia, S.S., Chatterjee, S., Pasha, M.L., Babu, S., Jat, M.L., López-Ridaura, S., Groot, J.C.J., Toorop, R.A., Barba-Escoto, L., Noopur, K., Kashyap, P., 2021. Farm typology for planning targeted farming systems interventions for smallholders in indo-Gangetic Plains of India. Sci. Rep. 11, 20978. https://doi.org/10.1038/s41598-021-00372-w.

Kostrowicki, J., 1977. Agricultural typology concept and method. Agirucult. Syst. 2, 33–45. https://doi.org/10.1016/0308-521X(77)90015-4.

Kuivanen, K.S., Michalscheck, M., Descheemaeker, K., Adjei-Nsiah, S., Mellon-Bedi, S., Groot, J.C.J., Alvarez, S., 2016. A comparison of statistical and participatory clustering of smallholder farming systems – a case study in northern Ghana. J. Rural. Stud. 45, 184–198. https://doi.org/10.1016/j.jrurstud.2016.03.015.

Kumar, S., Craufurd, P., Haileslassie, A., Ramilan, T., Rathore, A., Whitbread, A., 2019. Farm typology analysis and technology assessment: an application in an arid region of South Asia. Land Use Policy 88, 104149. https://doi.org/10.1016/j.landusepol.2019.104149.

LaFevor, M.C., 2022. Characterizing agricultural diversity with policy-relevant farm typologies in Mexico. Agriculture 12, 1315. https://doi.org/10.3390/agriculture12091315.

Landais, E., 1998. Modelling farm diversity: new approaches to typology building in France. Agric. Syst. 58, 505–527. https://doi.org/10.1016/S0308-521X(98)00065-1.

Lopez-Ridaura, S., Frelat, R., Van Wijk, M.T., Valbuena, D., Krupnik, T.J., Jat, M.L., 2018. Climate smart agriculture, farm household typologies and food security. Agric. Syst. 159, 57–68. https://doi.org/10.1016/j.agsy.2017.09.007.

Madry, W., Mena, Y., Roszkowska-Madra, B., Gozdowski, D., Hryniewski, R., Castel, J. M., 2013. An overview of farming system typology methodologies and its use in the study of pasture-based farming system: a review. Span. J. Agric. Res. 11, 316–326. https://doi.org/10.5424/sjar/2013112-3295.

Moreno-Pérez, O.M., Arnalte-Alegre, E., Ortiz-Miranda, D., 2011. Breaking down the growth of family farms: a case study of an intensive Mediterranean agriculture. Agric. Syst. 104, 500–511. https://doi.org/10.1016/j.agsy.2011.03.007.

Pacini, G.C., Colucci, D., Baudron, F., Righi, E., Corbeels, M., Tittonell, P., Stefanini, F. M., 2014. Combining multi-dimensional scaling and cluster analysis to describe the diversity of rural households. Ex. Agric. 50, 376–397. https://doi.org/10.1017/S0014479713000495.

Ruben, R., Pender, J., 2004. Rural diversity and heterogeneity in less-favoured areas: the quest for policy targeting. Food Policy 29, 303–320. https://doi.org/10.1016/j.foodpol.2004.07.004.

Shukla, P., Agarwal, A., Gornott, C., Sachdeva, K., Joshi, P.K., 2019. Farmer typology to understand differentiated climate change adaptation in Himalaya. Scientific Report 9 (1), 20375. https://doi.org/10.1038/s41598-019-56931-9.

Sinha, A., Basu, D., Priyadarshi, P., Ghosh, A., Sohane, R.K., 2022. Farm typology for targeting extension interventions among smallholders in tribal villages in Jharkhand state of India. Front. Environ. Sci. 10, 823338. https://doi.org/10.3389/fenvs.2022.823338.

Thar, S.P., Ramilan, T., Farquharson, R.J., Chen, D., 2021. Identifying potential for decision support tools through farm systems typology analysis coupled with participatory research: a case for smallholder farmers in Myanmar. Agriculture 11, 516. https://doi.org/10.3390/agriculture11060516.

Tittonell, P., Muriuki, A., Shepherd, K.D., Mugendi, D., Kaizzi, K.C., Okeyo, J., Verchot, L., Coe, R., Vanlauwe, B., 2010. The diversity of rural livelihoods and their influence on soil fertility in agricultural systems of East Africa – a typology of smallholder farms. Agric. Syst. 103, 83–97. https://doi.org/10.1016/j.agsy.2009.10.001.

Valbuena, D., Groot, J.C.J., Mukalama, J., Gérard, B., Tittonell, P., 2015. Improving rural livelihoods as a "moving target": trajectories of change in smallholder farming systems of Western Kenya. Reg. Environ. Chang. 15, 1395–1407. https://doi.org/10.1007/s10113-014-0702-0.

Wollburg, P., Tiberti, M., Zezza, A., 2021. Recall length and measurement error in agricultural surveys. Food Policy 100, 102003. https://doi.org/10.1016/j.foodpol.2020.102003.