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Towards actionable farm typologies: Scaling adoption of agricultural inputs in Rwanda

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ABSTRACT

Rollout of development interventions using a one-size-fits-all model can achieve economies of scale but neglects to account for variability in farm and farmer characteristics. A data-driven approach to incorporate farmer diversity in scaling strategies may help to achieve greater development impact. However, interpreting the multiplicity of smallholder characteristics is complex, time-consuming, and the ways in which the insights gained can be implemented is poorly understood. Navigating these tensions, we present a farm typology study carried out in collaboration with a large development organisation (the "scaling partner") promoting agricultural inputs in Rwanda. This study was conducted late in the scaling pathway, in order to finesse the scaling strategy, rather than to target intervention selection. Drawing on nearly 3000 interviews from 17 districts of the Western, Southern, and Eastern Provinces of Rwanda, the typology differentiates households along two axes: 1. prosperity (a cornerstone of conventional typologies), and 2. adoption of inputs (fertilisers and improved crop varieties). We used an efficient household survey tool, a minimum-variable approach, and concepts from the study of adoption of agricultural innovations. Through an action-research collaboration with the scaling organisation we adapted the methods and the findings to be "actionable.

Approximately two-thirds of the study population were using fertilisers and improved seed to some extent. Along each prosperity stratum, however, there were multiple degrees of adoption, demonstrating the value of including adoption information in typology constructions. Ten farm types were identified, where the key differences along the prosperity axis were land area cultivated and livestock owned, and the key differences along the adoption axis were perceptions of input efficacy, access to training, and education level. We also present a simple decision tree model to assign new households to a farm type. The findings were used in three ways by the scaling organisation: (i) characterisation of the population into discrete groups; (ii) prioritisation, of farm types for engagement, and geographical locations for further investment; and (iii) design of decision support tools or re-design of packages to support technology adoption for specific farm types. The need for field-level validation of the typologies was also stressed by the scaling organisation.

1. Introduction

Agricultural interventions usually aim to increase agricultural production, and to improve other issues related to sustainable development such as human welfare, food security, incomes, and environmental conditions. However, the scaling of such technical interventions to realise these benefits is not a simple process. Technologies are typically developed and proven to be feasible under controlled (often experimental) settings. Technologies are then tested under diverse biophysical, socio-economic, and cultural contexts and selected based on their performance under these experimental conditions. The scaling phase then begins, where technologies are trialled in real-world settings (often

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on working farms). During the scaling phase, farmers decide if they will adopt the innovation, may dis-adopt, and may share their decisions with others. Institutional support measures, such as communications, knowledge exchange, and financial instruments are employed during the scaling phase, while institutional collaborations implement (Notenbaert et al., 2017; Westermann et al., 2018; Shilomboleni et al., 2019).

Organisations can use two broad classes of strategies at the scaling phase (Wigboldus et al., 2016). One strategy is the "one-size-fits-all" approach which delivers an intervention to the largest number of people possible, assuming that the technical potential of the intervention and the correct basket of facilitating conditions will lead to widespread uptake and impact. The benefits of the one-size-fits-all strategy are the potential for economies of scale, and that it does not rely on hard-to-acquire data relating to the viability of the intervention in different physical or social environments. The second strategy can be termed the "tailored approach", which takes account of various contextual factors and nuances that influence adoption and intervention impact. Mutually reinforcing benefits of the tailored approach include higher rates of technology uptake (Haile et al., 2017) and greater benefits from technologies best-suited to the local environment (Vanlauwe et al., 2016). However, the high initial cost of conducting research required for the tailored approach increases the risk that the return on investment is not viable. This article reports on an attempt to "tailor" the scaling strategy of a large-scale agricultural development organisation, drawing on the study of adoption, using the method of farm typologies, and conducted in an action-research manner.

A substantial literature on the adoption of agricultural innovations in the rural development context centres around the Theory of Diffusion of Innovations. The theory dominates academic discourse on adoption decisions and the spread of technologies through a population. Scholars (e.g. Pannell et al., 2006; Beaman et al., 2018) have elaborated on the theory first proposed in 1962 (Rogers, 1962), to establish models of technology diffusion at distinct stages of adoption (Wigboldus et al., 2017). Sociological and economic research have been the main contributors to a list of subjective and profit maximizing variables that may explain adoption decisions (Feder et al., 1985). This list of possible determinants, drivers or obstacles relevant to the adoption process is extensive (e.g. Doss et al. 2003; Bidogeza et al., 2009; Mudombi, 2013; Ogada et al., 2014; Tshikala et al., 2015), prompting the authors of one review to state that "It seems that in the empirical literature every measurable characteristic of farms and farmers has been found to be statistically related to some measure of adoption of some innovation" (Pannell et al., 2006). Examples include the objectives of the decision maker and perceived relative advantage by the decision maker, the feasibility of conducting and trials and learning from those, education and skill on the part of the decision maker, farm size, land tenure, market access and functioning, labour availability, access to credit, attitude to risk (Feder et al., 1985; Pannell et al., 2006; Jack, 2011). It has been argued that although the suitability of innovation to the farm context (e.g. climatic, soil, topography) is of vital importance, such factors are technical prerequisites rather than related to the adoption-decision process (Sumberg, 2005). Our survey instrument was informed by this list of adoption-related factors although this study does not aim to identify the variables correlated with adoption but rather to establish the variables that discriminate adoption levels in our research setting.

Farm typologies developed out of the discipline of farming systems analysis to make sense of the heterogeneity observed between regions (Dixon et al., 2001) and within regions (Kruseman et al., 2006; Wilkus et al., 2019). The basic premise is to group households with other households who share similar characteristics, forming a distinct "type" which can be compared against other "types". This practice is for the purpose of identifying an agricultural technology or other development intervention which might benefit one type but not another – for the "targeting" of agricultural innovations (e.g. Tittonell et al., 2009; van der Ploeg et al., 2009; Giller et al., 2011). Farm typologies are usually based on structural and functional farm characteristics such as farm size, livestock ownership, crops grown, agricultural productivity, household size, and labour availability; biophysical characteristics such as climate, altitude, or soil type; economic characteristics such as total income, assets owned, market engagement, farm-based income, and non-farm income; and resource use characteristics such as use of fuel, inputs, labour, credit, and so on (Tittonell et al., 2005a; Tittonell et al., 2005b; Frelat et al., 2016; Wilkus et al., 2019). There are few examples of farm typology studies which explicitly address the study of adoption (e.g. Hammond et al., 2017a), although the argument has been made that this should be done more frequently (Meijer et al., 2015). The variables used for typology delineation are selected with the justification that they are relevant to the setting (Giller et al., 2011), and aim (Mądry et al., 2013) of the research and development effort. Recent methodological guidelines recommend hypothesis-led selection of a long list of variables which may be context relevant, and then selection of the most useful based on multi-variate analysis techniques (Alvarez et al., 2018, Wilkus et al., 2019). Despite the valuable contributions of farm typology analysis to theoretical understanding and the potential use in targeting technologies, there are relatively few published examples of such typologies being verified in the field (e.g. Kuivanen et al., 2016a), and even fewer which actually evaluate the use of typologies by an implementing organisation (Wilkus et al., 2019).

Drawing on the method of farm typologies, and insights from the study of adoption of agricultural innovations, the study was co-designed in partnership with a large rural development organisation called One Acre Fund (referred to as "the scaling organisation"). We carried out a household survey, and created a typology incorporating farm structure, economy, and adoption variables. Upon discussion of the results with the scaling-organisation, we then developed a decision tree to rapidly assign new households to one of the farm types. Working closely with the scaling organisation was critical to design knowledge products which met their needs for further use, and which laid the foundation for a subsequent evaluation of their use of the typology and other results. Such a research configuration has been deemed essential in articles exploring how to re-orientate traditional agricultural research to deliver more actionable, scalable knowledge products, whilst establishing the relationships for quick adoption of those knowledge products (Schut et al., 2014; Coe et al., 2016). Providing any objective evaluation of the scaling organisation's activities was outside the scope of this paper, as was any exploration of the pros and cons of NGO/third party engagement in national extension efforts either in general (Feder et al., 2011) or specifically in Rwanda (Clay and King, 2019).

This article entails three research goals. First, to evaluate the information gained by including adoption observations to further differentiate households compared to conventionally constructed typologies (i.e. typologies based purely on farm structure and function). Second, to evaluate the use of decision trees as a method of providing a user-friendly tool for characterising farmers. Third, to extend the application of typology methods farther along the scaling pathway than previously reported.

2. Materials and methods

2.1. Study context

The national agenda for agricultural development in Rwanda is described in the 20-year plan "Vision 2020", which entails increased use of agricultural inputs such as fertilisers, liming agents, and improved varieties (National Institute of Statistics of Rwanda, 2012; National Institute of Statistics of Rwanda, 2015; Cyamweshi et al., 2017; Kathiresan, 2011; Rwibasira, 2016). The scaling organisation collaborator in this research was the non-profit social enterprise One Acre Fund, founded in 2006, which supplies smallholder farmers with credit, training, and quality-assured inputs, with the aim to build enduring prosperity. The organisation currently serves more than 800,000 smallholder farmers in Kenya, Rwanda, Burundi, Tanzania, Uganda and Malawi (see www.oneacrefund.org). Their program offers micro-credit to smallholder farmers to buy agricultural inputs (and some other products), delivering those products close to farmer's homes, often in remote areas. The scheme provides inorganic fertilisers (NPK, DAP, and Urea), improved seeds (maize, bush beans, and climbing beans), a liming agent called travertine, solar powered lamps, as well as agricultural training, advice, and literature promoting good agricultural practices (such as line planting, compost use, and timely weeding), and business training through a group liability model. Participation in the program lasts for one growing season (approximately 6 months) after which the farmer may choose to sign up again if they wish. Enrolment is open to all smallholder farmers, and there is no intentional targeting of the scheme towards specific sub-groups of farmers within the communities where they operate. As of 2018, over 270,000 farming families in Rwanda were enrolled with their services. Household enrolment rates reached 37% of the population in the Western province, 25% in the Southern province, and 17% in the Eastern province (according to estimates from the scaling organisation and population figures from the National Institute of Statistics of Rwanda, 2012). The scaling organisation was active in five districts in the Western province, and although the duration of their engagement differs per district, activities were in operation by 2012 across the province. In the Southern province the organisation was active in five districts, starting in 2013; and in the Eastern province active in five districts, starting in 2015.

2.2. Site selection and sampling

Data for this study was collected in the 15 districts where the scaling organisation operated at the time of the study: five districts in the Eastern Province, five districts in the Southern Province, and five districts in the Western Province (Table 1). Additionally, two districts were included where the organisation was not activite: Ruhango in the Southern Province and Kirehe in the Eastern Province. These locations were chosen to take a wide geographic spread thus capturing more of the variation in farming systems, and sampling from areas where the scaling organisation had been active for different time periods, thus capturing different stages in the promotion and adoption cycles.

Sample sizes were calculated based on the minimum sample size needed to detect a statistically significant difference between farmers in each of the provinces (with a 95% confidence level and 5% margin of error). We assessed the population size of each district and each province, and estimated the minimum sample size required for six indicators of interest, and drew on means and variance of the indicators of interest from other (unpublished) studies in Central or East African countries using the same survey tool to interview smallholder farmers. Those indicators were gross calorific food availability per household per year, cash income USD PPP per person per day, farm size per household, livestock holdings per household, family size, and a compound indicator for innovation capacity (based upon value orientations, responses to hypothetical scenarios, reported changes made on farm, and changes planned for the future, adapted from Hammond et al., 2017a). A minimum sample size of 160 interviews per district was predicted to be sufficient. In each of the districts where the scaling organisation was operating, 80 farmers who were enrolled in the program and 80 non-enrolled farmers were selected for interview. Two-stage cluster sampling was performed to select respondents; 15 randomly selected cells (sub-district groupings of villages) were selected in each district. Following cell selection, households participating in the scaling organisation's program ("enrolled households") were selected randomly from enrolment lists; non-enrolled households were identified through a quasi-random process whereby enumerators were instructed to go the centre of each village and then use a randomly generated cardinal direction and random number '*n*' as a guide to visit the n[th] house in the specified direction. The selection process was repeated until the desired number of interviews was achieved for that cell. In total, 2720 farming households were selected for interview. Due to non-available households and non-available replacements, a total of 2710 interviews were achieved during June and July 2018. The number of interviews conducted per district is presented in Table 1.

The purposive over-sampling of farmers enrolled in the scaling organisation's scheme was to provide sufficient data on adoption behaviour, in order to generate a typology covering the full range of the adoption spectrum in the study sites. To establish the distortion effects of over-sampling enrolled households, we compared land area cultivated, land area owned, livestock owned, and family size between the enrolled and non-enrolled populations using *t*-tests and found that only livestock ownership differed significantly between the two groups, with enrolled farmers owning 0.9 Tropical Livestock Units (TLU) compared to 0.6 TLU. This implies some self-selection bias in enrolment with the scaling organisation, and therefore the sample is not completely representative of the communities studied. With these caveats in place, we argue that the descriptive data is a valuable contribution to the sparse literature covering Rwandan farming systems, as the differences in asset profiles between the two groups were minor. However, the prevalence of farm types with high enrolment rates might be over-represented. To correct this, we randomly subsampled from our data, correcting the ratio of enrolled households and non-enrolled households to the levels of enrolment as recorded in the scaling organisation's records at the district level.

Table 1
Number of households interviewed in each province and district.

Province	District	Enrolled households	Non-enrolled households	Total Interviews
Western	Karongi	82	75	157
	Ngororero	80	79	159
	Nyamasheke	86	74	160
	Rusizi	89	70	159
	Rutsiro	83	78	161
Southern	Gisagara	74	85	159
	Huye	77	82	159
	Nyamagabe	82	78	160
	Nyanza	85	75	160
	Nyaruguru	95	65	160
	Ruhango	0	159	159
Eastern	Gatsibo	77	84	161
	Kayonza	74	86	160
	Kirehe	0	160	160
	Ngoma	87	73	160
	Nyagatare	73	87	160
	Rwamagana	38	118	156
All Provinces	All Districts	1182	1528	2710

Enrolment refers to participation in the scaling organisation's program of agricultural support at the time of the survey.

2.3. The survey tool and variables collected

The household survey was carried out using the Rural Household Multi-Indicator Survey (RHoMIS) (Hammond et al., 2017b), adapted for use in this study context. The tool is a modular survey and analysis package which captures the common data required to understand farm system management, productivity, livelihoods, and human welfare, in the context of agricultural development work. The data quality on crop yields and incomes was of comparable quality to other widely used surveys operating in the similar environments (Fraval et al., 2018). The use of internationally recognised indicators and the user-centred design supports efforts to build coherent data from many independent research or development projects, reduce the time spent on survey design and the lag between collection and reporting (van Wijk et al., 2020; van Etten et al., 2017; Rosenstock et al., 2017; Kristjanson et al., 2017).

The variables gathered included household composition, physical farm characteristics, management, production, amount and sources of income, uptake of promoted interventions, perceptions and sources of information regarding those interventions, distance to markets and agricultural input suppliers, attitudes towards farming, gendered control of production, and food security indicators such as dietary diversity (FAO and FHI 360., 2016) and food availability (Frelat et al., 2016). The questionnaire was implemented by trained Rwandan enumerators who used a digital platform for data collection and aggregation (Hartung et al., 2010). Enumerators visited respondents at their homes, following prior arrangement using local contacts such as government or scaling organisation extension officers or local administrators. Interviews were conducted by a single enumerator and usually a single respondent, who was often the household head, or another senior member of the household who felt competent to respond on behalf of the entire household; and the average interview lasted 1 h (± 20 min). The vast majority of the interview questions were based on respondent recall over a 12 month period and relating to the entire farm-household output or livelihood (i.e. questions were not asked at plot level or individual level). The questionnaire is available from the authors upon request.

2.4. Analyses

2.4.1. Variable selection for typology generation

Following methodological guidelines for farm typology creation (Alvarez et al., 2018; Wilkus et al., 2019), we drew up an extensive list of 48 variables based upon literature regarding structural, functional, and economic farm characteristics commonly used in farming systems analysis, and variables commonly found to relate to adoption of agricultural innovations, as well as the actual adoption level reported in the survey. Drawing on knowledge of the sites, logic, and assessment of correlations, a shortlist of variables was made. Shortlisted variables were explored through principal component analysis (PCA; Jolliffe, 2002), and then through iterative clustering. Principle component analysis was conducted separately for each province to identify variables with greatest explanatory power (most strongly correlated with principle components), and exclude those variables with weaker explanatory power, high regional variation, or logical overlap with other explanatory variables. We then transformed continuous variables into binary indicators (for example instead of measuring amount of maize produced as a continuous variable we used the binary classification of maize planted/not planted), and repeated the PCA and clustering iterations using those binary variables in a step-wise manner. Where a binary variables resulted in an outcome of equal or higher predictive power than the continuous variable it was retained and the continuous variable discarded. This was done so that the variables used in the typology definition should be as simple as possible. Influenced by the “minimum data” approach (Steinke et al., 2019), the following selection criteria were applied: to select the fewest variables which explain the majority of variation in the survey data, and that those variables should be easy to collect. Ease of collection was defined as data not considered sensitive by the respondent, and which the respondent did not find challenging to recall in a level of detail allowing for meaningful differentiation of households.

This process led to selection of six variables for typology formulation:

(i) the household grew maize, bush beans, and climbing beans (yes/no);
(ii) the household owned at least one cow (or the equivalent amount of livestock in TLU; yes/no);
(iii) the land area cultivated (ha);
(iv) marital status of household head (single/married);
(v) the household head had received any formal education (yes/no); and
(vi) The number of perceived positive changes in the last 4 years relating to farm and livelihood (count).

The sixth variable requires some additional explanation. Respondents were asked whether they had observed an increase, decrease, or no change in their land area cultivated, crop harvests, crop diversity, input use, sales to markets, and off farm incomes, over a 4-year period. They were then asked if they had wanted that change to occur. The respondent's perception of the frequency and desirability of change served as an indicator for innovation capacity and facilitating conditions; both prerequisites for adoption.

2.4.2. Cluster analysis for typology generation

The selected variables were then used as inputs for cluster analysis, using the partitioning around medoids method (PAM; Reynolds et al., 1992), which permits identification of actual observations which best exemplify the characteristics of that cluster. The dissimilarity matrix calculations used the Gower method, which allows for numerical, ordinal, and categorical data (Gower, 1971). Silhouette width (the metric to determine the explanatory power of clusters when using the PAM method) was highest for 19 clusters. A substantial jump in silhouette width was observed at ten clusters, which was determined to provide the best balance of explanatory power and ease of interpretation. Ten farm types is more than typically reported in such typology studies, justified by the two axes of interest in this study – farm system prosperity and adoption of interventions – as well as the large spatial area covered.

Interpretation of the clusters was performed by exploring average values and variance for numerical indicators, and differences of proportions of observations (counts per cluster) of responses to binary or categorical variables. Medians were used when summarising the study population, and means were used when comparing farm types, as they better illustrated differences between the farm types. Significance testing between clusters was done using pairwise Wilcoxon rank sum tests for continuous variables and the chi squared test for counts of binary variables. All cash values are given in US$ adjusted to 2015 purchasing power parity, using World Bank rates (Piburn, 2018). Data was compiled and analysed in the R software environment (R Core Team, 2018), using appropriate packages: ade4 (Dray and Dufour, 2007), cluster (Maechler et al., 2018), dplyr (Wickham et al., 2018), ggplot2 (Wickham, 2016). This process was performed across all regions and within regions.

2.4.3. Decision-tree development

Through consultation with the scaling organisation, a decision tree model was selected as the tool that would be developed for field operatives to quickly determine an individual's farm type, and then offer more precisely targeted services and advice. The variables used in the cluster analysis were used to develop the decision-tree for classifying individual respondents into their farm types. The model used recursive partitioning and splitting criteria to derive pathways to uniquely identifiable classes of a desired variable (Nisbet et al., 2009). Development of the decision-tree model followed two standard steps: training and classification (Ben Amor et al., 2006). The scaling organisation prioritised six of the ten farm types for inclusion in the decision tree, which consisted of 1636 household observations. To train the model we randomly selected 80% ($n = 1309$) of these shortlisted households. We trialled two packages for creation of the decision tree, both in the R software environment: RandomForests (Liaw and Wiener, 2002) and rpart (Therneau and Atkinson, 2019). Both packages delivered similar results, and the results from rpart are presented. The rpart package identifies the variable which discriminates most between farm typologies, partitioning the data on this variable, and then identifies splitting criteria which maximise the separation in the data into distinguishable sub-groups. This process is then repeated until all farm types (sub-groups) are uniquely distinguishable. The trained model was then tested on non-trained data (325 households) to measure its accuracy in classifying households into types, compared to the outputs of the cluster analysis.

Table 2
Summary of farm characteristics of all locations studied.

	All Provinces	Southern Province	Western Province	Eastern Province
Cultivated Land (ha)	0.3 (0.5)	0.23 (0.4)	0.22 (0.8)	0.5 (0.8)
Livestock Owned (TLU)	0.29 (0.55)	0.2 (0.43)	0.25 (0.45)	0.46 (0.82)
Family Size (members)	5 (3)	4 (3)	5 (3)	5 (3)
Three most common crops (% hh growing)	Maize (81%), Bush Beans (68%), Sweet Potato (67%)	Sweet Potato (80%), Maize (71%), Bush Beans (67%)	Maize (78%), Climbing Beans (76%), Sweet Potato (71%)	Maize (93%), Bush Beans (91%), Cassava (54%)
Three most common livestock (% hh owned)	Cattle (50%), Goats (41%), Chicken (24%)	Cattle (54%), Goats (42%), Pigs (28%)	Cattle (57%), Goats (33%), Pigs (23%)	Goats (47%), Cattle (39%), Chicken (26%)
Crop Diversity	6 (4)	6 (4)	6 (4)	6 (5)
Livestock Diversity	1 (1)	1 (1)	1 (0)	1 (1)
Value of Crop Produce	100 (300)	80 (250)	150 (250)	150 (530)
Value of Livestock Products	0 (310)	0 (320)	0 (320)	0 (170)
Value of Off Farm Income	0 (3)	0 (0)	0 (25)	0 (0)
Months Food Insecure	3 (2)	3 (1)	3 (2)	3 (2)
Household Dietary Diversity Score (0 − 10)	5 (3)	4 (3)	4 (4)	5 (2)

Medians are shown, and brackets indicate inter-quartile ranges. The time period is 1 year. All values relate to USD PPP 2015.

3. Results

3.1. Farm system summary

In the regions studied, farm sizes were typically very small (median 0.3 ha), and 84% of households farmed less than 1 ha. Livestock ownership was also generally low, and cattle ownership appeared to indicate a step-change in wealth, where households who owned a cow were considerably wealthier than those who did not. The major crops cultivated were maize, beans, sweet potato, cassava, vegetables, banana, cocoyam, and sorghum. The median number of crop species planted was 6, and the median number of livestock species owned per household was 1. See Table 2 for a summary of the farm systems.

In general, food security was poor and incomes were low, especially for farmers without livestock. Off-farm income was uncommon, and the main source of income was sales of crops and livestock. Farms on average sold 32% of all production, although 28% of households did not sell any farm-produced items. The common cash crops were maize and bush beans, and the commonly sold livestock items were live cattle, live goats, and cows' milk. Overall, households relied primarily on self-produced foodstuffs and had one or two distinct sources of income.

3.2. Use rates of promoted technologies

Table 3 presents the proportions of households who reported using specific agricultural inputs, the average rates at which those inputs were applied, and also the scaling organisation enrolment rates and average duration of enrolment at province level. Urea and DAP were the most heavily used fertilisers, used by 50–60% of households. Less commonly used was NPK, ranging from 14 to 27% of households. Improved seed (for maize, bush beans, and climbing beans) was used by about 40% of households, without much variation between provinces. The liming agent Travertine was uncommon, used by 6–12% of the study population. Enrolment rates with the scaling organisation are presented for the study sample but are not representative of the wider population. Duration of enrolment shows greater variation between the provinces, following the pattern which may be expected given the scaling organisation's duration of engagement in each province.

3.3. Farm typologies

Ten farm types were identified through cluster analysis. The ten clusters can be conceptually organised along two axes: 1. increasing wealth and, 2. increasing adoption of the promoted technologies (inorganic inputs and improved seed, Fig. 1). Within a single wealth stratum, there is substantial variation in the degree of adoption.

Table 3
Summary of the variables related to adoption of the promoted technologies.

	All Provinces	Southern Province	Western Province	Eastern Province
Urea users (%)	54	49	61	53
Urea (kg/ha)	67 (149)	100 (243)	71 (167)	50 (95)
NPK users (%)	22	26	27	14
NPK (kg/ha)	167 (383)	208 (476)	167 (329)	111 (325)
DAP users (%)	55	49	64	54
DAP (kg/ha)	93 (201)	114 (259)	86 (196)	83 (160)
Improved Seed users (%)	39	37	41	39
Improved seeds (kg/ha)	40 (83)	56 (119)	45 (100)	25 (55)
Travertine users (%)	8	8	12	6
Travertine (kg/ha)	417 (1278)	797 (2245)	662 (1405)	100 (207)
Enrolment (%)	48	46	58	42
Enrolment duration (years)	1.3 (2.0)	1.2 (2.0)	2.0 (3.5)	0.8 (1.5)

Percentage values relate to the proportion of households interviewed who reported using each input. The values relating to input application rates or duration in years are medians, and the values in brackets are inter-quartile ranges. The medians and inter-quartile ranges are calculated only from the households who reported using those inputs, households who did not use those inputs were excluded. Travertine is a liming agent.

Summary information comparing the farm types for structural farm characteristics and adoption characteristics are provided in Tables 4 and 5. Farm types are described below following the layout in Fig. 1, moving from bottom-left to top-right.

3.3.1. Lower wealth stratum

Households in the lower wealth strata were further distinguished into 5 typologies that spanned adoption levels. Households in types 1, 2, and 3 were the poorest, they cultivated very small plots of land (< 0.3 ha), and the total value of all their household produce and incomes was generally less than 500 USD per year. They also had low enrolment rates with the scaling organisation. Households in types 1 and 2 did not to cultivate maize but focused on roots, tubers, and beans. Few households in types 1 and 2 used inorganic inputs or improved seed and believed the efficacy of such inputs was low compared to other farm types. Farm type 1 (9% of the represented population) reported more crop sales than type 2, had a higher proportion of educated household heads, and reported better access to agricultural advice, but poor access to agricultural training sources. Farm type 1 showed the lowest level of enrolment with the scaling organisation of any farm type. Farm type 2 (9%) had very low value of crop produce, low levels

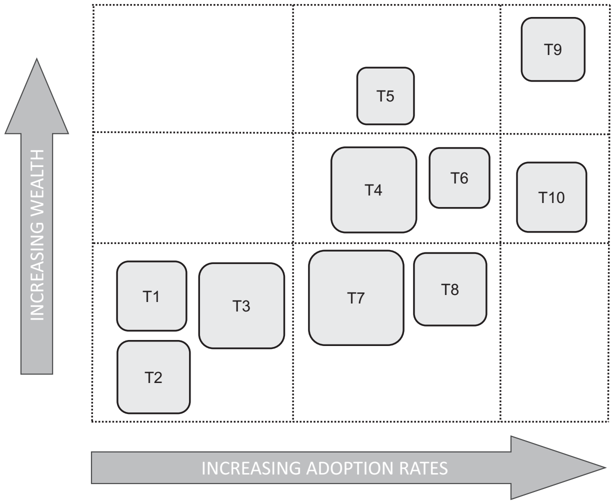

Fig. 1. The farm types plotted along two axes: the horizontal axis shows an increasing degree of adoption of inorganic inputs and improved seed, and the vertical axis shows a gradient of wealth. The dashed lines imply step changes between farm types along those axes. The sizes of the boxes for each farm type indicates the predicted prevalence of that farm type, relative to one another.

of education, similarly poor access to agricultural training, low levels of enrolment with the scaling organisation, and also had the least positive outlook, as measured by perceptions of previous changes which had occurred and future plans. Farm type 3 (13%) was also very poor but was more engaged with maize agriculture and inorganic inputs, although adoption rates were still low compared to other farm types. The household heads were usually single women with no education and very little land. Their perceptions of input efficacy was low and access to agricultural training or advice opportunities was limited. Farm types 1, 2 and 3 assessed their current conditions and expectations for the future as more bleak than other types; and crop yields and cash income were significantly lower than others.

Farm types 7 and 8 were also very poor, and although their land sizes were slightly larger than farm types 1, 2, and 3, their total value of produce and incomes were similar. However adoption rates among types 7 and 8 were higher than those of types 1, 2, and 3, with about half of the households reporting use of DAP, urea, and improved seed, and about half of the households enrolled onto the scaling organisation's program. Types 7 and 8, perceived access to agricultural training as higher than types 1, 2, and 3; although education rates of household heads were very low. Farm types 7 and 8 were very similar to one another. The most prominent difference was that type 7 (17% of the population) grew bush beans, while type 8 (9% of the population) grew climbing beans (each of which were used as inputs for the cluster analysis).

3.3.2. Middle wealth stratum

Households within the middle wealth strata were further classified into three groups with distinct adoption levels. Farm types 4 and 6 had moderate levels of wealth relative to other types, and moderate levels of adoption. Both cultivated land areas of around 0.65 ha, and had total value of activities over 1000 USD per year. Farm type 4 (13% of the study population) derived the majority of their income from cropping, but also had relatively strong off farm incomes, high levels of education, and had incomes supplemented by off-farm activities. Use rates of inputs and improved seed were fairly high, as was access to agricultural training, although enrolment with the scaling organisation was not markedly high. Farm type 6 (7% of the study population) focused more heavily on livestock production than on crops, evidenced by the relatively higher annual value of livestock produce compared to crops. Nevertheless, more than half of the households engaged in crops sales and adoption rates of the promoted inputs were slightly higher than that of type 4. Households in type 6 were in the highest strata for enrolment with the scaling organisation and for duration of enrolment.

Farm type 10 (9% of the study population) had moderate levels of prosperity, with cultivated land area on average 0.5 ha, livestock ownership 0.6 TLU and total value of activities around 1000 USD per year. Farm type 10 showed the highest rates of use of promoted inputs and the highest rates of enrolment and duration of enrolment with the scaling organisation. They reported a high degree of access to agricultural training, many positive plans for the future, and reported having made a high number of positive changes to their livelihoods and farm management.

3.3.3. Upper wealth stratum

Households in the upper wealth strata were further differentiated into two groups with distinct adoption levels. Households in farm type 5 (6% of the study population) were relatively prosperous. Cultivated land was 0.7 ha, the households owned on average two cows (1.9 TLU), and the average total value of activities was close to 3000 USD per year. Households in type 5 derived substantial income from crops, livestock and off farm activities. Use rates of the promoted inputs, and enrolment rates and duration with the scaling organisation, were all moderate.

Farm type 9 (7% of the study population) was the most prosperous. Households in this type owned more land and cultivated more (0.9 ha) than all other types, livestock ownership (1.9 TLU), and in terms of total value of activities (in excess of 3000 USD per year). They also showed high rates of adoption of the promoted inputs, and a high proportion of households selling crops and livestock products. Farm type 9 can be conceived as being distinct from all the other farm types due to the high asset base and rates of commercialisation. Enrolment rates with the

Table 4
Structural characteristics of the farm types.

Farm type	Land Cultivated (ha)	Heads of Livestock (TLU)	% married*	% educated*	Total Crop Value	Total Livestock Value	Annual Non-Farm Income	% sell crops*	% sell livestock produce*	Number of income sources
T1	0.3^{a}	0.4^{a}	82	72	290^{ab}	10^{a}	35^{abcd}	38	12	1.1^{ab}
T2	0.2^{b}	0.5^{a}	64	14	160^{a}	40^{ab}	88^{abc}	29	16	1.1^{a}
T3	0.3^{a}	0.4^{a}	0	12	250^{b}	110^{bc}	53^{d}	55	18	1.3^{ab}
T4	0.6^{cd}	0.3^{a}	90	100	730^{cd}	120^{cd}	101^{abc}	72	26	1.9^{cd}
T5	0.7^{c}	1.9^{b}	87	0	1040^{ce}	1850^{e}	118^{d}	74	50	2.2^{c}
T6	0.7^{cde}	1.5^{c}	80	20	420^{d}	1170^{f}	79^{acd}	58	43	1.9^{cd}
T7	0.5^{de}	0.4^{a}	100	0	390^{d}	70^{bc}	74^{abc}	64	22	1.7^{d}
T8	0.4^{a}	0.4^{a}	75	0	240^{b}	140^{bcd}	72^{ab}	40	21	1.4^{b}
T9	0.9^{f}	1.9^{b}	91	100	1560^{e}	1910^{e}	88^{cd}	84	61	2.9^{e}
T10	0.5^{e}	0.6^{d}	88	100	570^{cd}	350^{d}	137^{b}	64	31	2.0^{cd}

All values are means or proportions. Means have been used rather than medians to better illustrate differences between farm types. Significant differences between clusters are shown by compact letter display for the continuous variables, and by asterisk for the proportional variables, using the threshold of $p < .05$. Cash values are reported as household annual values in USD purchasing parity power adjusted (to 2015 values).

Table 5
Adoption and engagement characteristics of the farm types.

Farm type	% enrolled*	Years enrolled	Perception of Input Efficacy (0–1)	% use Urea*	% use DAP*	% use NPK*	% use travertine*	% use Improved Seed*	Access to agric. Training (%)*	Access to agric. Advice (%)*	% with positive future plans*	Positive changes in last 4 years (count)
T1	11	0.2^{a}	0.3^{a}	13	13	14	2	2	28	86	77	1.1^{a}
T2	18	0.3^{ab}	0.3^{a}	12	18	14	5	2	16	73	65	0.9^{a}
T3	28	0.8^{b}	0.4^{b}	38	36	10	3	26	39	78	69	1.3^{b}
T4	45	1.2^{c}	0.6^{cd}	62	63	22	8	48	62	91	89	2.4^{c}
T5	54	1.6^{de}	0.6^{cd}	63	63	25	5	41	67	93	90	2.5^{cd}
T6	66	2.1^{df}	0.7^{ce}	73	76	32	12	49	66	93	89	3.0^{de}
T7	40	1.0^{c}	0.6^{f}	52	52	16	4	41	61	90	83	2.6^{cd}
T8	44	1.3^{ce}	0.6^{df}	62	65	21	10	42	52	89	77	1.9^{f}
T9	61	1.9^{df}	0.7^{cde}	72	73	34	13	55	68	96	94	3.5^{eg}
T10	67	2.3^{f}	0.7^{e}	80	82	40	21	63	70	93	89	3.8^{g}

All values are means or proportions. Means have been used rather than medians to better illustrate differences between farm types. Significant differences between clusters are shown by compact letter display for the continuous variables, and by asterisk for the proportional variables, using the threshold of $p < .05$. Enrolment refers to participation in the scaling organisation's agricultural support program.

scaling organisation and duration of enrolment were also high.

3.4. Spatial distribution of the farm types

The distribution of farm types between provinces was non-random (chi squared test, $p < .001$). Certain types were more prevalent in certain provinces, as shown in Fig. 2 (excluding Kirehe and Ruhango, the two sampled districts with no scaling organisation presence). There was substantial variation in adoption behaviour between the three provinces, especially evident in farm Types 2, 6, 8 and 10, which were rare in the Eastern Province and common in the Western province. Type 7 was more prevalent in the Eastern and Southern Provinces than the Western Province, due to geographical preferences for climbing beans and bush beans. The prosperous mixed farming type 5 was more prevalent in the East, whereas the less prosperous livestock focused type 6 was relatively rare in the East compared to the other locations. This all underlines the importance of spatial context factors, such as geographic, socio-economic, and cultural variables (which were not addressed in this study). It also illustrates that the spatial context factors can influence adoption rates at least as heavily as they influence farm structural characteristics. For example, the Eastern Province is generally drier and flatter, with a greater agricultural focus on livestock than on cropping; in contrast to farming activities in the Southern and Western Provinces which have historically focused on crops, and where the geography is hillier and wetter. The differences in adoption rates may relate to such geographical factors, but also may also be a consequence of the availability of governmental extension services, or the level of extension services provided by the scaling organisation.

The predicted prevalence of the farm types where the scaling organisation had no historical activities is plotted in Fig. 3. In Ruhango there is a greater prevalence of the poorest and lowest adopting households compared to Kirehe, where there are more households in farm types further along the adoption gradient and higher up the wealth spectrum.

3.5. Farm typology decision tree

In communication with the scaling organisation, six farm types were selected to be of specific interest for immediate follow-on work: types 1, 2, 3, 6, 7, and 9. This was based partly upon perceived need (i.e. poverty – types 1, 2, 3, 7) and partly upon pragmatic decisions about the geographic location of farm types (types 6 and 7), the degree of investment in crop-related activities (i.e. to exclude heavily off-farm or livestock dependant farm types), and the degree to which farm types may be expected to achieve further adoption (i.e. to exclude households with high baseline levels of adoption). Farm type 9 was included due to a perceived potential by the scaling organisation and local leaders. Prioritisation was necessary for managerial decisions by the scaling organisation, but also served to simplify the restrictions set for the decision tree model. The decision tree is presented diagrammatically in Fig. 4. Five questions were used in the tree, all with binary responses, and with a maximum chain length of four questions to allocate the

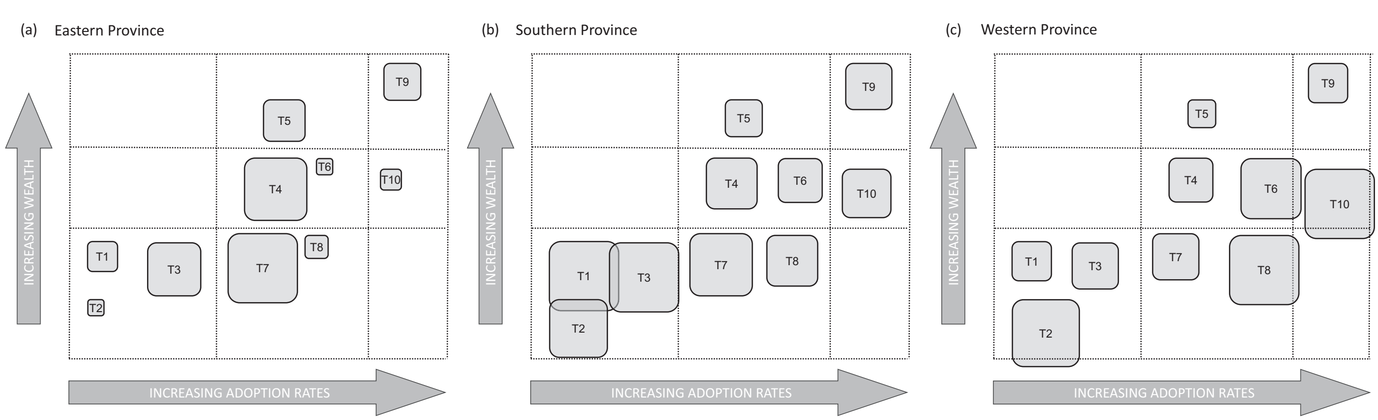

Fig. 2. Farm types among the districts sampled in the Eastern, Southern, and Western Provinces. The size of the boxes are scaled according to the predicted prevalence of the farm types. The provinces may be conceived of as representing a time series, as the Eastern province has received the least engagement from the scaling organisation promoting inputs, the Southern province received the middling degree of engagement, and the Western Province received the longest and greatest degree of engagement. However, the provinces also contain geographical, agricultural, and economic differences, which also account for an unknown amount of the differences seen here.

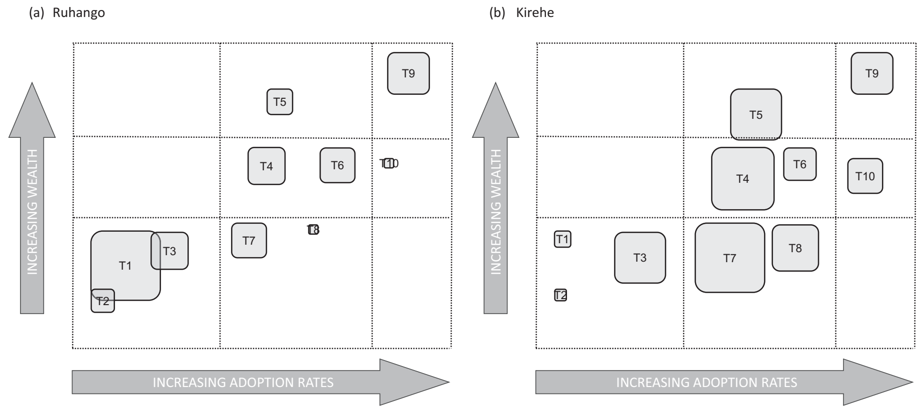

Fig. 3. The size of the boxes represents the predicted prevalence of the farm types in two districts where there has been no previous promotion of inputs by the scaling organisation, and in which they were considering establishing activities. Such information may be useful in defining investment priorities.

household to a farm type. The decision tree accurately classified 83% of households into the correct farm type, as defined by the cluster analysis. The major sources of error were along the adoption axis misclassifying type 1 and 2 households as type 3 (where marital status created bias); misclassifying type 1 households as type 2; misclassifying type 7 households as type 1 or 2; and misclassifying type 9 households as type 6. Wealth strata was correctly predicted in the majority of cases. The decision tree with all ten farm types was also constructed (not presented), but achieved a lower accuracy score (65%) and involved many more steps.

3.6. The use of the typology findings by the scaling organisation

The results presented here were discussed and refined in collaboration with the scaling organisation, taking account of their instrumental needs. The use of the above results by the scaling organisation can be conceptualised in three stages: characterisation, prioritisation, and design/re-design. Characterisation consisted of describing key features of the farming system, and separating farms into meaningful groups, to be compared or contrasted with one another. Prioritisation consisted of using the characterisation to guide future investments by the scaling organisation, targeted towards either a subgroup of the population (one or more of the farm types), or targeted spatially, according to the prevalence of certain farm types. While prioritisation was a key interest for the scaling organisation, it was also clear that firm decisions would not be taken until the typology had been verified by further field-level validation work.

The design of three new procedures was discussed: a validation

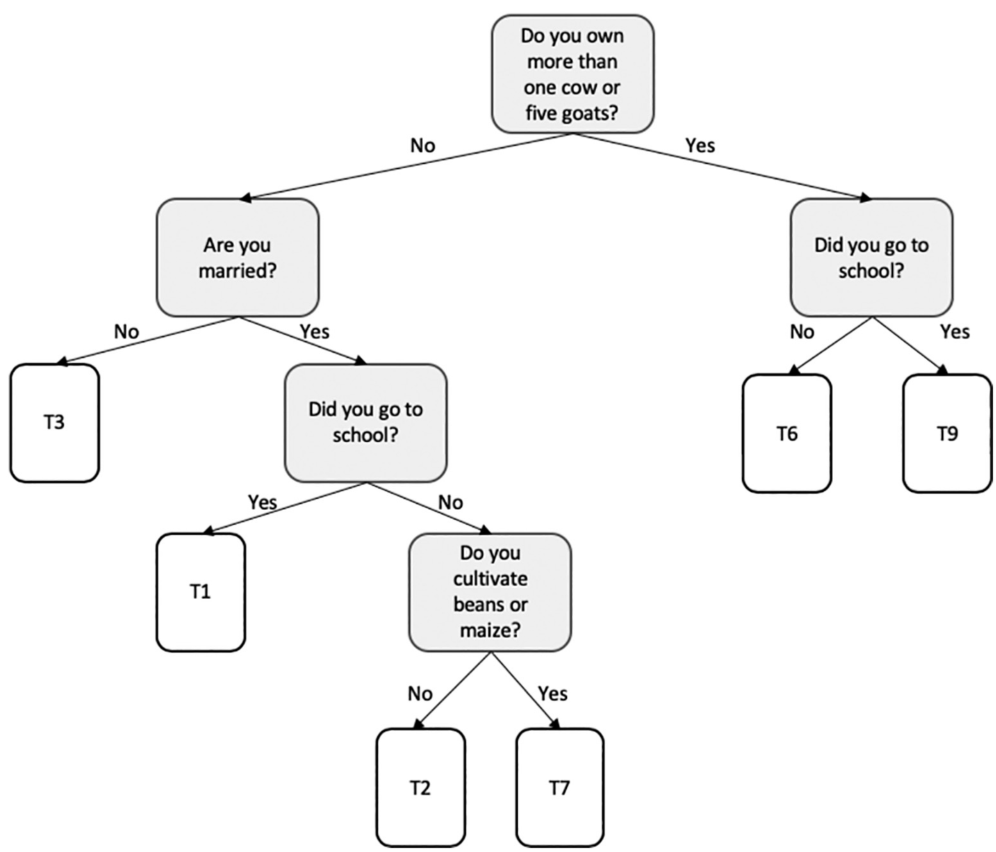

Fig. 4. Diagrammatic representation of the decision tree model used to identify farm types 1, 2, 3, 6, 7, and 9.

study for the typologies, a decision-tree for rapid allocation of households to a farm type, and a system for linking farm types to recommended technologies or recommended technology-support packages. Topics for re-design centred around the tailoring of technology-support packages towards different farm types, depending on their needs and obstacles to adoption. Along the lowest wealth stratum, farm types 1, 2 and 3 required access to agricultural training, although the mechanism of engagement likely differs between the groups. Farm types 1 and 2 did not grow any maize (all other types did). Farm type 3 was composed of single female-headed households, and so would be subject to gendered dynamics that tend to place severe constraints on time/labour availability, income, and possibly social stigma for such households. Taking into account these obstacles when designing packages geared towards farm types 1, 2, or 3 would therefore be required. Types 7 and 8, although on the poorest stratum, were well engaged with input use and the scaling organisation's activities. They would be better served by improved training on methods to increase crop productivity, geared towards their educational level. The re-design of promotional media describing best-practices and available technologies tailored to the educational levels of different types was a widely applicable recommendation.

4. Discussion

4.1. Extending typologies along the scaling pathway

The use of typologies to inform the scaling of development activities is an under-researched area. There is a tendency in the literature to use typology-based analyses to characterise populations and then to make intervention or targeting suggestions based upon these characterisations – but there is very little published work which studies how those insights are taken up and applied by implementing organisations. Such a pattern is evident in the literature for Rwanda: there are relatively many studies which characterise the farming system or the adoption process, but few which report on how that knowledge was used.

Characterisations of Rwandan farming systems in the literature (Klapwijk et al., 2014; Franke et al., 2016; Paul et al., 2018; Clay and King, 2019) are in accordance with this study: most farmers cultivate very small plots of land, grow a diverse range of crops, and about half owned at least one cow, or two or more goats. Most farmers relied primarily on crops for sustenance and income, and had little to no surplus income. Livestock ownership was the single variable most associated with increased prosperity of households and farm types (types 5, 6, 9). Land area alone did not appear to drive prosperity, and land area did not appear to be strongly associated with productivity, implying that management of the crop land was at least as important as the total land area available, or that land quality was an important factor. In terms of characterising adoption, the most important variables found in the present study were perception of input efficacy, access to agricultural training (Asfaw and Admassie, 2004), and a minimum asset base consisting of land area under cultivation, livestock, and income (Nkonya et al., 1997). Education among household heads was not strongly associated with adoption, as some moderately-adopting farm types had very little education; although the highest adopting farm types did have higher education rates (Tenge et al., 2004). Across all farm types the perception of input efficacy was found to be highly correlated to input use, which underlines the importance of promotional media, outreach, and extension services (Davis et al., 2012; Hamilton and Hudson, 2017); and is probably related to literacy. In a study on the drivers of smallholder agricultural adoption in Rwanda (Bidogeza et al., 2009) the major factors identified were sex of the household head, age, education, literacy, off-farm activity, household size, farm size and land tenure. Despite differences in study context, we identified some similar farm types, most notably marginalised female-headed households, higher-adopting mid-wealth households with more household members (labour) and higher incomes, and the wealthiest households with relatively large plots of land and livestock herds. We found higher adoption rates however, which could be explained by the location of the respective studies, activities of the scaling organisation in our study locations, and the over-sampling of enrolled households. Such information is useful in the design of broad-brush agricultural interventions but more nuance is required to finesse the scaling model beyond “one-size-fits-all”.

The use of such characterisation information in prioritising development investments is more commonly discussed in general terms, for example focussing on general trends in poverty dynamics (Dorward et al., 2009; Tittonell et al., 2009; Barrett et al., 2006). The prioritisation considered by the scaling organisation in this study entailed some logical similarities to the academic discourse, but also entailed some more pragmatic concerns. Prioritisation of farm types with low wealth (used a proxy for “need” of development), low adoption, and specific farm/livelihood strategies followed the assumption that if constraining conditions were removed, households would adopt (Dorward et al., 2008), and therefore welfare would improve. Access to agricultural training were very low for farm types 1, 2, and 3 (a common constraint, see Asfaw and Admassie, 2004), implying a failure in the delivery or accessibility of the scheme for those farm types, in turn implying the need for some re-design. Prioritisation was not done solely on the basis of poverty or lack of access to training. Type 9 were the most commercially oriented, highest yielding, and largest farms, and were selected for further investigation as their developmental needs were assumed to be quite different to other types, and therefore might require intervention packages to be re-designed in a quite different way.

An illustration of the scaling organisation's more pragmatic concerns relates to which farm types should *not* be prioritised for further support (a topic very rarely discussed in scientific literature). Farm types 7, 8, and 10, had low asset ownership and crop-orientated livelihoods, but relatively high adoption rates, so they were deemed lower priority for further attention. From a research perspective, it could be useful to evaluate what factors influenced progression from types 7 or 8 to the more prosperous and higher-adopting type 10 (anecdotally, the role of diligent plant management was reported by field-staff). However, from a pragmatic perspective, farm types 7, 8, and 10 had already received the intervention on offer and other farm types had not, so were perceived to be in greater need of the limited resources available.

Pragmatic prioritisation was also discussed on a spatial basis, at province level and at district level. At province level, differing prevalence of farm types could be used to modify strategy for that province. Types 1 and 2 were relatively common in the Southern and Western provinces, but not in the East. Therefore any re-designed intervention support packages for those farm types would not be relevant in the Eastern province. Investments in new districts could also be informed by farm type prevalence (Fig. 3). Ruhango district had a greater prevalence of the poorest and lower-adopting households compared to Kirehe, where farm types further along the adoption gradient and higher up the wealth spectrum were more prevalent. Ruhango therefore provided more scope for impacting the “poorest of the poor” through introduction of agricultural inputs. In Kirehe there were already established input use patterns, so development efforts may be more usefully pitched towards breaking the “glass ceiling” into the upper tier of smallholder prosperity.

The design of a validation study for the typologies was high on the agenda for the scaling organisation. This is logical if potentially expensive decisions were to be based on such a typology, and reflects another key difference between purely scientific typologies and the application of typologies to inform strategy at scale – the degree of certainty must be higher. Such validations studies are rarely carried out in academic work (e.g. Kuivanen et al., 2016a).

The Characterise-Prioritise-Design process observed here has some resemblance to the DEED model proposed by Giller et al. (2011): Describe-Explain-Explore-Design (see also Descheemaeker et al., 2019).

The DEED model however is intended to be used for intervention selection, whereas the process described here occurred further along the scaling pathway – a suite of interventions had already been chosen and a large infrastructure developed around disseminating those interventions. At this stage in the scaling process the question is not so much "what interventions would fit best" but "what can be done to achieve greater impact with the already chosen interventions". Answering this latter question might require some re-orientation of farm typology methodologies.

4.2. Benefits and shortfalls of the decision tree model

The co-design of the decision tree in accordance with the scaling organisation's prioritised farm types, the maximum chain of four simple questions, and the fairly high accuracy of classification, all point towards a robust and user-friendly tool. However the tool has not yet been tested in the field, and the typologies on which it is based have not yet been validated. Before the tool could be considered ready for use or robust such field tests must be carried out.

The decision tree opens up various opportunities for deployment. It could be used to rapidly sample large numbers of households, providing improved information on prevalence of farm types. Short questions related to perceived barriers to adoption or perceived needs could be integrated into the decision tree interviews for adaptive management. Repeat samples of a population could be carried out to identify household movement across farm types over time to better understand household dynamics. Finally, and perhaps more contentiously, the decision tree could be used for field staff to tailor services on-the-spot for their clients; providing specific recommendations for specific farm types (Douxchamps et al., 2016; Kuivanen et al., 2016b). This entails some risks, such as the misallocation of an individual to a type and therefore the wrong measures being recommended; or the intentional decision to treat some farm types more favourably than others, either by the individual implementing the decision tree interview, or by biased program design. Despite these risks the improved targeting capacity gained by such an approach is worth further exploration.

One potential obstacle to the wider use of such typology-derived decision trees is that quite sophisticated mathematical techniques are required for the multivariate analyses, clustering and tree delineation. Although resources are freely available to aid in typology construction (e.g. Wilkus et al., 2019), scaling organisations wishing to pursue such a method may have to hire in expertise, as often analytical capacity is lower in implementing organisations compared to research organisations. Whilst this is a barrier, it also presents an opportunity for collaboration between researchers and scaling organisations. Furthermore it points to a need for the development or testing of simplified methods (or perhaps software) which would allow such analyses to be conducted without specialised expertise.

4.3. The transience of typologies

A further issue to consider is the shelf-life of such a typology and decision tree. Some typologies are designed to provide highly generalisable insights (e.g. Dorward et al., 2009), and thus retain relevance for a longer period of time and in more places. In contrast, the typology described here was purposefully designed to be context specific, providing insights relevant to a specific situation and a specific point in time. Thus as the context changes, the typology and decision tree may become less and less accurate. Indeed, the objective of the typology and decision tree is to increase the rate at which development actors can facilitate change; so ironically a good typology may become obsolete quicker than a poor one.

The transience of typologies draws attention to a few needs for further work. Methods for adapting typologies or monitoring household movement across typologies can and should be developed in anticipation of community dynamics (Valbuena et al., 2015). Future research questions might include: for how long should a given typology remain relevant, and is there some way to assess the best-before date? How can improvements in data collection methodologies or data sharing systems provide more up-to-date information for analysis? And how can analytical methods facilitate more actionable insights, to capitalise capitalise on the knowledge generated in a timely fashion?

4.4. Input use, adoption, and subsidy programs

Some insights may also be relevant to broader discussions on input subsidies and uptake in the smallholder context. We observed fertiliser use rates which were quite high for the African smallholder context – those who applied fertilisers often did so in excess of 100 kg of product per ha (see Table 3). This could be due in part to the small land areas cultivated and the fact that fertilisers are generally sold in large sacks: it has been shown that with access to cheap fertiliser some farmers will consider the application rate to be "one sack one plot" (Yunju et al., 2012). There is evidence that inputs in combination with higher yielding varieties lead to greater use of fertilisers and greater yield outcomes (Matsumoto, 2014; Vanlauwe et al., 2016); we observed that farm types who reported more fertiliser use also reported greater improved seed use, which points towards a synergy. Some typologies evaluating input use (Chikowo et al., 2014) and soil fertility (Franke et al., 2016), found strong links between wealth and use of inputs and soil fertility. We did not find such a strong association. We found that there was a general trend that wealthier households adopted more inputs, but that within wealth strata differing degrees of adoption were observed. Despite the potential benefits, concerns have been raised that the blanket promotion of such technologies may exclude farm systems with distinct characteristics, increase inequalities and undermine resilience of the households who cannot or do not want to take part (Clay, 2018; Clay and King, 2019).

The targeting of specific farm types for agricultural support mechanisms is widely practiced, often with the explicit intention of targeting one of the poorest groups (Jayne et al., 2018), such as female headed households, farms with small land area, or in the case of the Rwandan governmental system the stratification according to various resource endowments (locally known as "Ubudehe", Klapwijk et al., 2014). Such mechanisms have been criticised as failing to lead to change for the targeted sub-groups due to the challenges of implementation (Jayne and Rashid, 2013) and elite capture (Jayne et al., 2018), and in some cases perverse outcomes identified where elite capture serves to further undermine the livelihoods of the poorest (Clay and King, 2019).The results of this study imply that consideration of both wealth status and the adoption characteristics along that wealth stratum might yield more beneficial outcomes; and that the methods exist to efficiently collect the data and carry out such an analysis.

5. Conclusion

This article began with the observation that "one-size-fits-all" development strategies are easier to scale-up but may be inefficient in terms of achieving adoption at scale when compared to more nuanced "tailored" approaches. We demonstrated that a farm typology considering adoption of technologies quite far along the scaling pathway could yield useful results to further tailor the scaling strategies for a large agricultural development organisation. We found that consideration of adoption delivered more nuanced findings than farm-related variables alone. The scaling organisation went beyond using the typologies for characterisation, demanding validation, and using the typologies to inform prioritisation decisions, and design targeted research tools and intervention support packages. We presented a simple decision tree model to rapidly assign an individual to a farm type for recommending interventions of support measures appropriate to that individual, or in assessing the prevalence of farm types in a study population.

We contend that all of these features demonstrate the utility of such a farm-adoption typology to refine large scale roll-out development activities – in this specific case the promotion of agricultural inputs. This paper did not prove whether such a tailored approach to program design really yields benefits over the one-size-fits-all model, but does lay some of the necessary foundations for such a study. The establishment of a working relationship between research and scaling organisations is an essential first step. The typology, decision tree, and observations made here are the second step. Next should come validation of the typology at ground level, and validation of the decision tree model. The scaling organisation would then need to use the tools and results as they see fit, and the research partner would need to study the process, to evaluate how they were used, and possibly to estimate a return on investment.

We urge researchers working with typologies to engage scaling partners so that the typology results can be applied and move beyond characterisation studies. This will entail some methodological development for easier typology definition and interpretation. It will also entail some innovation in terms of understanding how scaling organisations use the tools, interpret the findings, and how they translate the findings into action, in order to deliver impact at scale.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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