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Research

Typology of smallholder maize farmers in South-Kivu, Eastern D.R. Congo: implications in improving farming practices and markets

Adrien Byamungu Ndeko[1,2] · Géant Basimine Chuma[1] · Marcellin Cuma Cokola[1] · Jean Mubalama Mondo[1] · Yannick Mugumaarhahama[1,3] · Espoir Bisimwa Basengere[1,4,5] · René Civava[1,5] · Gustave Nachigera Mushagalusa[1]

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Abstract

Understanding the typology of smallholder maize farmers is crucial to elucidate the diversity in local farming systems, and therefore, devise effective interventions and policies that maximize the impact of agricultural innovations in South-Kivu province, eastern Democratic Republic of Congo (DRC). This study aimed at characterizing maize farmers in South-Kivu province and clustering them based on various socioeconomic and agronomic factors to identify specific production constraints and devise more effective interventions. A household survey among 300 South-Kivu maize farmers allowed to identify four distinct clusters based on farm size, land use, income, and agricultural technology adoption. The clusters ranged from resource-poor smallholder (Types 1 and 2) to medium-resource semi-innovative producers (Type 3) and highly equipped innovative farmers (Type 4). Key discriminative factors included total farm size, maize farm size, farming experience, access to agricultural credit, income, and innovation adoption rate. This study revealed specific constraints for each cluster, including low soil fertility, poor weed management, low market access, and labor scarcity. This study's findings demonstrate the value of farm typology in guiding targeted interventions to address specific constraints and improve maize productivity, and suggest specific strategic directions for research and development projects in rural areas of the South-Kivu province.

Keywords Typology · Maize farm · Agricultural innovations · Production constraints · South-Kivu

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1 Introduction

Due to its crucial role in improving national economies and reducing poverty and food insecurity among the population, the agricultural sector play a vital role in driving economic and social development in sub-Saharan African countries [64], including the Democratic Republic of the Congo (DRC) where agriculture employs over 70% of the population and contributes more than 40% to the gross domestic product (GDP) [40]. In South-Kivu province, located in eastern DRC, smallholder farmers with land plots, averaging 50 acres, form the backbone of the agricultural sector [22, 53]. Maize (*Zea mays* L.) holds significant importance in the region, serving as a crucial crop for food security, income generation, and poverty reduction among smallholder farmers' households. The territories of Kabare, Walungu, and Uvira are the primary maize producing areas within the province [40].

Despite its importance, maize yields among smallholder farmers in South-Kivu remain low, with an average of ~ 0.8 t ha^{-1}, in stark contrast to the potential yield of 5 t ha^{-1} recorded in other countries (FAOSTAT, 2022). Low maize yields among smallholder farmers in South-Kivu have been attributed to several major constraints, such as lack of adoption of effective soil fertility management practices, low adoption of improved varieties, widespread crop diseases and pests, and limited access to quality seed [10, 29, 41, 42].

To address these challenges, governmental agencies, research centers, and non-governmental organizations (NGOs) have introduced and promoted innovative agricultural practices and technologies to smallholder farmers. These interventions included the adoption of improved maize varieties, implementation of soil fertility management techniques, erosion control practices, and improved crop disease management approaches (Seed system Group 2019; [12, 65]). These initiatives aimed to enhance maize yields and contribute to the overall development and well-being of smallholder farmers in the region.

The adoption of agricultural innovations that can impact maize yields is influenced by various factors such as farmers' socio-economic characteristics, production objectives, access to resources, and interaction with government extension services [20, 54]. These factors contribute to a significant level of heterogeneity among farmers, which must be thoroughly understood within a specific region to facilitate the adoption of agricultural technologies [23, 27]). It is equally important to consider this heterogeneity when targeting and disseminating innovative technologies in rural areas. However, in South-Kivu province, there has been a lack of consideration for the existing heterogeneity among farmers in the dissemination campaigns of new agricultural technologies, leading to low adoption rates among farmers [33, 41].

For instance, a study by Chuma et al. [12] reported low adoption rates of soil fertility management practices and increased soil degradation in Kabare, despite farmers having some knowledge of these practices, which have been prevalent in the region for a long time. Similarly, studies conducted by Mushagalusa et al. [46] and Mondo et al. [41] found low adoption rates of improved varieties of major crops like maize and cassava in Kabare, Kalehe, Idjwi, and Walungu. In the case of maize, [49, 50] reported low adoption rates of improved varieties in Kabare, Walungu and Uvira, despite multiple extension campaigns initiated by government services and NGOs. Understanding the factors that explain technology adoption and maize yield variability among farmers requires considering the heterogeneity of farmers in terms of socio-economic characteristics and crop management practices, as argued by Dutta et al. [16]. In this context, conducting a typological analysis of farms allows for identification of farmers or farms sharing similar characteristics, facing common constraints, and having similar production objectives, to thereby studying their diversity and heterogeneity [23].

Identification and characterization of production systems play crucial role in simplifying the diversity of producer groups and enabling site-specific technological interventions and policy proposals. Moreover, employing this approach facilitates a better understanding of the factors influencing the adoption or rejection of agricultural technologies. To accomplish this, farmers need to be categorized into specific homogeneous groups based on specific criteria, such as technical and socio-economic factors, depending on the objectives of the characterization aimed at creating a typology of farms [45, 58]. Different criteria have been proposed by authors for differentiating farmers, including financial capital, access to land and production diversification, [7, 27]. However, in South-Kivu Province, few studies have attempted to characterize farms through categorization, and even fewer have considered socio-economic factors, crop management practices, and production constraints. There is a lack of information regarding the utilization of farm typologies for characterization and targeted interventions [49, 50].

This study was initiated with the aim of characterizing and categorizing maize producers from a representative sample of 300 households, and categorizing them to better understand their heterogeneity. The objective is to

promote the adoption of agricultural innovations based on the identified typologies and to guide policymakers' interventions in a more targeted and effective manner in the South-Kivu province and making a valuable contribution to the existing literature on farm characterization for targeted intervention in the South-Kivu province. More specifically, (i) we conducted a comprehensive typology analysis of maize producers to identify the main groups within the study area; (ii) we identified and reported the key socio-economic factors and production constraints experienced by farmers according to identified typologies, and (iii) we proposed appropriate interventions to address the raised constraints.

2 Methodology

2.1 Study area

This research was conducted in South-Kivu Province, eastern DRC, focusing on three selected territories: Kabare, Walungu, and Uvira (Fig. 1). These territories were chosen because they are known for extensive maize cultivation by smallholder farmers [10, 46] and are located in three distinct agroecological zones. They cover an area of ~ 6906 km². Kabare is located between 28° 45′ and 28° 55′ East (Longitude) and between 2° 30′ and 2° 50′ South (Latitude) with an elevation ranging from 1460 to 3000 m above sea level (m.a.s.l). The mean annual rainfall is approximately 1601 ± 154 mm, and the average monthly temperature is 19.67 ± 2.3 °C [19].

Walungu lies between 28.44° and 28.758° East (Longitude) and between 2.692° and 2.625° South (Latitude) with elevation ranging from 1000 m (at Kamanyola) to 3000 m.a.s.l. The average annual rainfall in Walungu is ~ 1600 mm, and the average maximum and minimum monthly temperatures are 25 °C and 18 °C, respectively [10, 59]. Uvira is located between 29° and 29° 30′ East and between 3°20′ and 4° 20′ South, and between 800 and 900 m.a.s.l. The average annual rainfall is 1500 mm. The average monthly maximum and minimum temperatures are 30.5 to 32.5 °C and 14.5 to 17 °C, respectively. Uvira has a semi-arid climate according to the Köppen-Vladimir climate classification.

Kabare and Walungu are bordered by the Kahuzi-Biega National Park, while Nyungwe Forest overhangs Uvira and Walungu. Conversely, Kabare and Uvira are bordered by the Lakes Kivu and Tanganyika, respectively [12, 44]). The presence of lakes and forests in the region contributes to bimodal rainfall pattern, resulting in a humid tropical climate with two distinct seasons. The first is a long rainy season lasting from September to May, followed by a short dry season from June to August. The rainy seasons determine two successive growing seasons for agricultural activities. The first growing season spans from mid-September to mid-January, while the second one extends from mid-February to mid-June [12, 51, 60]. Maize is the predominant cereal crop cultivated in the area, with an estimated cultivation area of ~ 151,627.27 ha during the 2018/2019 cropping season [10].
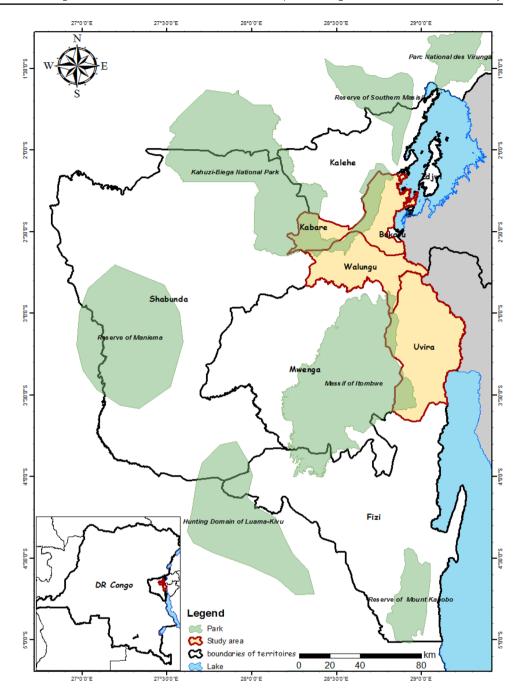
2.2 Farmer household survey and data collection procedures

The survey to establish the cluster typology was conducted in twelve villages across the three predefined agroecological zones (AEZ). These areas were chosen due to the significance of maize in terms of its economic, social, and nutritional importance. Moreover, these areas serve as operational sites for various NGOs and local, national, and international research centers, such as the International Institute of Tropical Agriculture (IITA), Harvest-Plus, and INERA-Mulungu, which are actively involved in promoting agricultural technologies to enhance crop production. To ensure a representative sample, four villages were selected per area, totaling twenty-five households randomly selected from each village, resulting in a total of three hundred households participating in the study. Data collection involved conducting individual interviews with farmers and organizing focus group discussions (FGDs) with local resource persons. The survey and FGDs took place during the 2020/2021 cropping season, and discussions with farmers focused on their experiences during the previous two cropping seasons, namely the 2019/2020 season B and the 2020/2021 season A (Appendix 1).

The research utilized a semi-structured survey questionnaire that incorporated key variables, which had been pretested in another area and approved by the local resource persons. The questionnaire aimed to gather both qualitative and quantitative information by addressing the identified key variables (Table 1). These variables included socio-economic characteristics of the households, agronomic characteristics, resource availability, constraints, and opportunities among farmers. Insights from previous studies conducted by Ndeko et al. [50] and Chuma et al. [12], which examined factors influencing the adoption of agricultural technologies in South-Kivu were incorporated into the questionnaire. The included factors were total farm size, total farm size under maize cultivation, level of education, engagement in

Fig. 1 Map of the South-Kivu province showing sites covered by the study in the selected territories (Kabare, Walungu, and Uvira)

off-farm activities, and source of income, access to agricultural credit, land tenure, soil fertility inputs, and soil fertility management practices. Furthermore, geographical coordinates of each farm were collected and linked to the farmer characterization information. Before to the survey, informed consent was obtained from the participating farmers. All methods were performed in accordance with the relevant guidelines and regulations. The design and implementation of the questionnaire adhered to the Clinical Nurse Specialist (CNS) Code of Ethics.

2.3 Typology construction

The typology of farms was conducted using a two-step methodological approach. The first step involved the selection of variables that would capture the diversity among farms. The second step involved selecting a multivariate analysis technique for the farm typology. In accordance with studies by Vall et al. [67] and Innazent et al. [23], both structural and functional characteristics encompass socioeconomic factors and farm size, while functional characteristics

Table 1 Description of the variables used in the principal component analysis (PCA) and CA (variables marked with an asterisk), and in the characterization of farm types

Variables	Codes	Units	Description	Mean ± SD or %
Socioeconomic characteristics				
Household size	HHS	Number	Number of household members	6.17 ± 3.11
Age of household head	HHA	Year	Age of the household (HH) head in years	39.12 ± 3.2
Gender (male)	Gender	Dummy	1 if HH head is male, 0 if otherwise	36.0
Education level (years)	EDLEV	Year	Number of years the HH head spent in formal education	5.6 ± 1.4
Labor (1 if only family members are involved in farm activities; 2 if family members and external labor, 3 if only external labor)	FLAB	Dummy	1: Family members only	28.7
			2: Family members and external labor	54.0
			3: External labor only	17.3
Farming experience*	FE	Year	Years of HH head experience in maize production	19.86 ± 6.12
Other income source than farming (yes)*	OBF	Dummy	1 if famer is engaged in off farm activities, 0 if otherwise	36.2
Access to credit*	ACC	Dummy	1 if famer has access to agricultural credits, 0 otherwise	43.2
Income from maize (1 if < 25%, 2 if from 25 to 49%, 3 if 50 to 75%, 4 if >75%) *	IFM	Dummy	< 25%	32.3
			25 to 49%,	35.1
			50 to 75%	20.6
			>75%	12.0
Land use				
Farm size*	FS	Are	Total land allocated to maize by HH	17.59 ± 1.3
Landholding size*	LHS	Are	Total land possessed by the farmer	34.4 ± 1.3
Land ownership (yes)*	LOW	Dummy	1 if the farmer owns the cultivated land; 0 otherwise	27.75
Maize farming attributes and agricultural innovations				
Type of maize variety used (1 if the farmer use local varieties, 2 if IMVs, 3 if both local and IMVs) *	TVU	Dummy	1: Local varieties	59.0
			2: IMVs	21.3
			3: Both local and IMVs	19.7
IMV Seed availability (yes)*	IMVSA	Dummy	1 if the IMVs are available; 0 otherwise	42.5
Origin of seed (1)	OS	Dummy	1 if farmer-saved and seed exchanges, 0 if from NGO and research center	57.9
Use of chemical fertilizers (1) *	UCF	Dummy	1 if farmer uses chemical fertilizers, 0 otherwise	9.03
Use of organic input (1) *	UOI	Dummy	1 if farmer uses organic inputs, 0 otherwise	77.6
Use of pesticides (1) *	UPEST	Dummy	1 if farmer uses chemical pesticides, 0 otherwise	31.0
Crop diversity (1) *	CDIV	Number	Number of other crops grown besides maize	2.5 ± 0.08
Cropping system (sole cropping) *	CSYST	Dummy	1 if sole cropping, 0 if mixed cropping	19.4
Number of associated crops*	NMIXC	Number	Number of other crops grown with maize	2.0 ± 0.05
Contacts with extension services*	CES	Dummy	1 if at least one visit per year from extension services; 0 otherwise	39.2
Field-to-house distance (far)*	FHD	Dummy	1 if the farm is far; 0 = otherwise (famers appreciations)	58.5
Constraints for maize production (Constraint Severity Index)				
Disease constraint status	DCS	Score	Disease score ranging from 1 to 3	2.33 ± 0.04
Low soil fertility	LSF	Score	Soil fertility score ranging from 1 to 3	2.2 ± 0.04

Table 1 (continued)

Variables	Codes	Units	Description	Mean ±SD or %
Lack of labor	LL	Score	Labor score ranging from 1 to 3	2.4±0.03
Lack of farmland	LFL	Score	Farmland score ranging from 1 to 3	2.4±0.03
Unavailability of quality seeds	UnQS	Score	Seed unavailability score ranging from 1 to 3	2.3±0.04
Unavailability of farm inputs	UnFI	Score	Farm inputs unavailability score ranging from 1 to 3	2.3±0.04
Lack of market demand	LMD	Score	Score ranging from 1 to 3	2.1±0.03
Post-harvest losses	PHL	Score	Score ranging from 1 to 3	1.9±0.03
Tax hassles	TH	Score	Score ranging from 1 to 3	1.7±0.04
Difficulty in weeding	DW	Score	Score ranging from 1 to 3	2.2±0.04

IMVs: Improved maize varieties. Summary statistics are presented as mean values± Standard deviations (SD) for each variable, variables marked with an asterisk (*) represent those used in the principal component analysis

including cropping systems, sources of income, and other non-farm activities. A total of 15 variables were selected for the farm typology, as outlined in Table 1.

The collected data were analyzed using principal component analysis (PCA) and cluster analysis to identify patterns and group similar farmers together. PCA was employed to reduce the key variables of the study into components that capture the maximum variability of information. It was applied on the groups of variables to determine the existing linear relationships between the variables [25, 44]. The selected groups of variables included socio-economic characteristics of the farmers, agronomic characteristics, resource availability, and production constraints (Supplementary material fig. 1). Before conducting PCA, a preliminary examination of the dataset was performed to assess the suitability of the technique. High correlation and independence between variables were considered important factors in determining the appropriateness of PCA for the dataset [7, 62]. To evaluate the suitability of PCA, two tests were conducted: the Bartlett sphericity test and the Kaiser-Meier-Olkin (KMO) test. The Bartlett sphericity test examined whether variables were significantly correlated, while the KMO test assessed the overall sampling adequacy. A KMO value greater than 0.6 and a p-value less than 0.05 for Bartlett's sphericity test indicated that the PCA method was suitable for the dataset. The selected variables were then used to construct principal components through PCA [24, 68]. Kaiser's "absolute" criterion was applied, retaining all factors (components) with eigenvalues greater than 1 [57]. Thus, the use of PCA allowed for a reduction in the dimensionality of the dataset while capturing the underlying patterns and relationships among the variables.

After applying PCA, six main components were retained, accounting for a cumulative variance of ~ 69.33% of the total variance in the dataset. The PCA was conducted using the FactoMineR package in the R software version 3.6.0. [26]. Interpretations of the selected components and their significance were facilitated by examining the correlations between the variables and the components. The scores of the principal components obtained from PCA were then used in the hierarchical classification using the Wald minimum variance method to determine the number of classes. This classification method grouped farms based on their similarity in relation to the selected variables [67]. The similarity among classes was measured using Euclidean distances. Subsequently, a non-hierarchical classification was performed to refine the number of classes obtained from the initial classification and to specify the distribution of farms within each class. The resulting classes directly corresponded to different types of maize producers or maize farms (Supplementary material fig. 2). The cluster analysis was performed using the "*cluster*" (version 1.15.2) package, and the results were visualized using the "*ggplot2*" package.

To further analyze the differences among farm types (clusters), an analysis of variance (ANOVA) was applied to the quantitative variables to identify variables that significantly contributed to the differentiation among farm types. The Tukey test (HSD) was used as post-ANOVA to determine which farm types were significantly different for each quantitative variable. For qualitative variables, the chi-square test was employed. A significance level of 0.05 was used for both tests. After obtaining the farm classes, a final characterization was performed by examining the mean values of each discriminant variable within each class. This analysis allowed for the identification of the distinctive variables that defined each class, leading to the naming of the classes based on their inherent characteristics.

2.4 Multinomial logistic regression analysis of Maize Producer Typologies

Multinomial logistic regression (MNLR) was employed to analyze the relationships between different typologies of maize producers and their socio-economic characteristics, agricultural practices, and maize production constraints in the study areas. The objective was to examine how various explanatory variables influence the classification of maize producers into different types or categories. It provides estimates of the effects of independent variables on the relative probability of belonging to each category of maize producers, while considering other explanatory variables included in the model [56]. Specifically, after defining the explanatory variables, each explanatory variable x was associated with a coefficient β in the model, indicating the strength and direction of the effect of each variable on the log-odds of belonging to each category compared to a reference category, Type 1. The odd ratios associated with each variable allowed to interpret the relative impact of a one-unit change in the explanatory variable on the odds of belonging to a category of maize producers relative to Type 1 as the reference. Finally, the p-values indicated the statistical significance of the estimated coefficients (β). P-values below the significance threshold (typically 0.05) suggest that the explanatory variable has a significant effect on the classification of maize producers into different categories [50].

3 Results

3.1 General characteristic of maize farms in South-Kivu

3.1.1 Socio-economic characteristics of maize farmer households

The survey showed that ~ 36% of respondents were men and 64% were women. The mean age of household heads was 39.1 years, while the mean household size was 6.1 persons. In this context, household members are an important source of family labor. In fact, about 28.7% of the households use only family labor for the different agricultural tasks, while 54% households use both family and hired labors. On the other hand, 17.3% of the households use only hired labor. The education level of the heads of households, estimated by the number of years spent at school, was 5.6 years on average, while their experience in farming maize was ~ 20 years. Maize farmers in South-Kivu have limited access to agricultural credit. Only 43.2% have easy access to agricultural credit. This low rate of access to agricultural credit pushes farmers into other non-farm income-generating activities (36.2%). Regarding income from maize, 32.3% of farmers report that less than 25% of their total income comes from maize production. About 20% of farmers report that maize production accounts for 50 to 75% of their monthly income and 12% for more than 75% (Table 1).

3.1.2 Maize farming attributes and agricultural innovations

The analysis of the maize cultivation characteristics in South-Kivu reveals important insights. Maize is grown on small plots with an average farm size of 17.59 ± 1.3 are out of a total farm area of ~ 34.4 are owned by households. This highlights the importance of maize cultivation in the region, which occupies about 50% of the total household farm size. It can also be observed that only 27.7% of the maize farmers are owners of the land they cultivate. In general, maize is grown in association with other crops (80.6%), depending on the farming objectives. The results show that about two crops are associated with maize across farms. While the number of other crops grown on the farm apart from maize is ~ 3 crops. The adoption of agricultural innovations, including improved varieties, soil fertility management practices, disease and pest management, and pesticide use, is relatively low among maize farmers. This may be attributed, in part, to limited access to extension services (39.2%), which play a crucial role in promoting the adoption of agricultural innovations. The majority of farmers (59%) rely on local maize varieties, while 19.7% use a combination of local and improved varieties, and 21.3% exclusively use improved varieties. The limited availability of improved maize seeds (42.5%) contributes to the low adoption rate. Farmers primarily obtain their seeds through seed saving or seed exchange from friends and neighbors (57.9%), with only 23.1% sourcing seeds from NGOs or research centers. Chemical fertilizer use rate is low, with only 9% of maize farmers using them, while 77.6% rely on organic matter for fertilization. In terms of pesticide use, 31% of producers employ chemical pesticides for crop disease and pest control.

3.1.3 Constraints for maize production in South-Kivu

The main constraints to maize production in South-Kivu are presented in Table 1. The most common constraints are diseases, low soil fertility, lack of labor, lack of arble land, limited access to quality seeds, lack of farm inputs, limited market access, difficulty in weeding, post-harvest losses and high taxes.

3.2 Typology of maize farmers in the South-Kivu province

The KMO and Bartlett's sphericity tests were used to check whether the data set of 300 farmers and 15 variables was suitable for PCA. The results of these two tests showed an overall KMO value greater than 0.57, while Bartlett's sphericity test was highly significant (p = 0.001), indicating that our data set was suitable for PCA.

From the 15 variables, six components were selected according to the Kaiser-Meir criteria. The first six selected components together expressed about 69.3% of the total variability of the dataset (Fig. 2a, b). The first component accounted for a good part of the total variance (22.4%) and was significantly and positively correlated with land size, farm size, access to credit and use of chemical pesticides. Farmers who own larger plots allocate large areas to maize
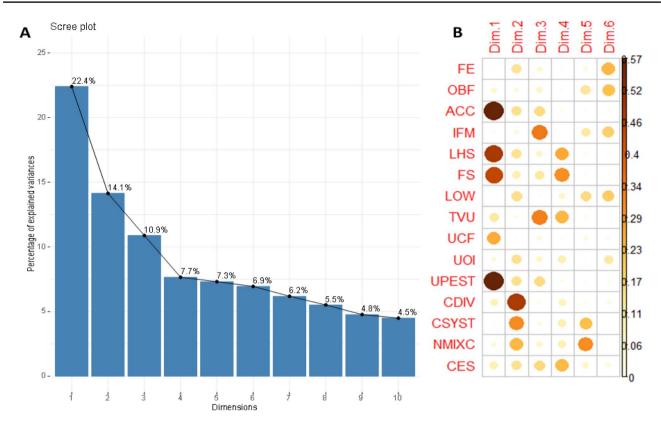
Fig. 2 Principal component analysis results: the scree plot defines eight values of each principal component (**A**) and the correlation plot shows the relationship between the principal components and variables (**B**)

cultivation and consequently use more chemical pesticides to control diseases and pests attacking the crop to limit losses. With relatively easy access to credit, such farmers can afford land for cultivation, either through purchase or lease, and other farm inputs, such as chemical pesticides (Fig. 3a).

The second component expressed 14.1% of the total variability in the dataset and was significantly and positively correlated with crop diversity (Fig. 3a). The third component expressed about 10.9% of the total variability of the data and was significantly and positively correlated with income from maize and the type of varieties used. From the results of the PCA, the more farmers use improved varieties, the more they benefit from this crop, which would normally be related to the yield gain from using improved varieties (Fig. 3b, Table 2). The fourth PC expressed 7.7% of the total variability in the dataset and was significantly correlated with the contact with extension services (Figs. 3c–g). For the fifth principal component, the results show that it expressed 7.3% of the total variability and was significantly and positively correlated with the number of crops associated with maize (Table 2, Figs. 3d–h). Finally, the sixth principal component expressed 6.9% of total variability, but no variable was significantly correlated with it. These results suggest that there is a possibility to generate categories of maize farmers using different variables (Fig. 3a–d, e–f). Hierarchical clustering results suggested four classes of farmers, while the non-hierarchical clustering method allowed a further distribution of individuals in the generated classes. Based on these results, we can conclude that maize farmers were grouped into four distinct classes, identified as maize farmer types, based on structural (resource) and functional (maize farming attributes and agricultural innovations) characteristics (Fig. 4a, b).

3.2.1 Type 1: Severely resource-poor farmers with a diversified cropping system, a small total farm area and a small area allocated to maize, non-innovators with a high contribution from maize to household income

Type 1 emerged as the most prominent group among maize farmers, representing ~ 40% of the respondents. This group stands out from the others based on various variables, including farm size (landholding size), maize cultivation area, crop diversity, cropping system, number of crops combined with maize, access to credit, variety selection, and use of farm inputs. Type 1 farmers exhibit distinct characteristics, such as possessing an exceedingly
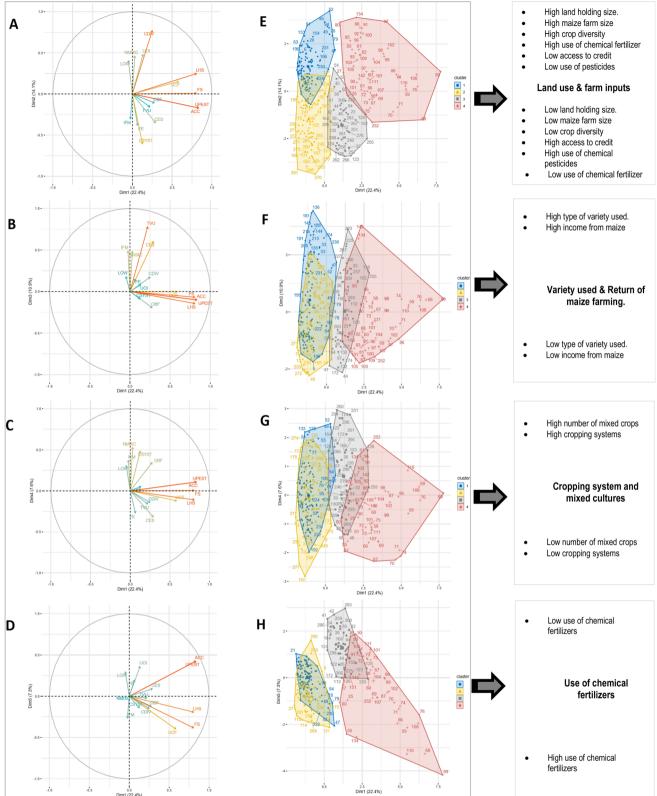
Fig. 3 PCA and CA results and outputs as represented by circles of correlation (**A**–**D**) and clusters which are in this case the different farm types 1–4 (**E**–**H**) in the planes PC1-PC2, PC1-PC3, PC1-PC4 and PC1-PC5

Table 2 Factor loadings from the four components resulting from the Principal Component Analysis with eigenvalues and percentages variance explained

Variables	Components					
	1	2	3	4	5	6
Eigenvalue	3.36	2.12	1.63	1.14	1.09	1.04
Variance accounted for (%)	22.39	14.13	10.88	7.65	7.31	6.95
Cumulative variance (%)	22.39	36.53	7.65	55.07	62.38	69.33
Farming experience	0.03	−0.37	0.21	0.08	−0.19	**0.48**
Off-farm activity	0.22	−0.19	−0.25	−0.07	0.36	**0.46**
Access to credit	**0.76**	−0.39	−0.40	0.12	0.08	−0.10
Income from maize	0.08	−0.17	**0.58**	0.03	0.34	−0.43
Landholding size	**0.69**	0.38	0.25	**−0.51**	−0.13	0.08
Maize farm size	**0.66**	0.31	0.35	**−0.55**	−0.08	0.07
Land ownership	0.01	0.39	−0.02	0.24	**0.42**	0.38
Type of maize variety used	0.34	−0.13	**0.57**	0.48	−0.12	−0.01
Use of chemical fertilizers	**0.50**	0.02	−0.18	0.10	−0.17	−0.12
Use of organic input	0.19	0.38	−0.25	0.15	0.04	−0.33
Use of pesticides	**0.76**	−0.39	−0.40	0.12	0.08	−0.10
Crop diversity	0.29	**0.69**	−0.12	0.28	−0.13	0.14
Cropping system	0.07	**−0.55**	0.15	−0.31	0.47	0.00
Number of mixed cultures	0.19	0.48	0.24	0.30	**0.55**	−0.03
Contacts with extension services	0.31	−0.38	0.40	**0.51**	−0.25	0.18

Bold values indicate significant correlations between the variables and the corresponding components

small total farm area, dedicating a limited area to maize cultivation, and practicing low crop diversity on their farms. They primarily engage in intercropping and combine maize with multiple other crops (more than 2). These farmers typically have less farming experience, averaging ~ 10 years, and predominantly rely on local varieties (16%), although some of these farmers use a combination of local and improved varieties. Type 1 farmers belong to the resource-poor category, facing limitations in accessing agricultural credit (0%), which also restricts their ability to purchase and utilize chemical fertilizers (0.54%) and pesticides (0%).
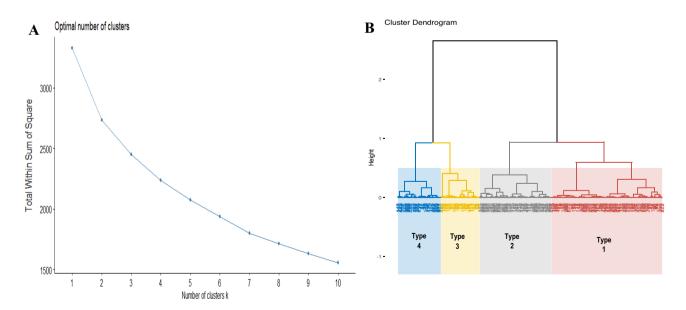

Fig. 4 Scree plot showing the optimal number of classes (**A**) and Dendrogram (right) displaying a range of cluster solutions resulting from Ward's method of CA and K mean analysis

3.2.2 Type 2: Resource-poor farmers with long experience in maize production, small farm size, small area allocated to maize and low innovation

Type 2 represents ~ 27% of the surveyed farmers. This group is distinguished from the others by several key variables, including experience in maize production, total farm area, maize farm size, crop diversity, number of crops grown with maize, cropping system, cultivar selection, access to credit, and use of organic matter. Farmers in Type 2 have a relatively small total farm area, with a limited portion allocated to maize cultivation. They have considerable experience in maize production, averaging ~ 19 years. Most farmers in this group practice maize monoculture (13.089%), while others combine maize with other crops (9.424%), typically involving one additional crop combined with maize. In terms of cultivar selection, some farmers exclusively use local cultivars (10.9%), while others exclusively use improved cultivars (6.9%). Additionally, a small portion of farmers combines improved and local cultivars (1.7%). Compared to Types 1 and 4, Type 2 farmers face challenges in accessing agricultural credit and consequently utilize fewer organic matter, chemical fertilizers, and pesticides.

3.2.3 Type 3: Moderately well-resourced and semi-innovative farmers with long experience in maize production, with a relatively small area and high use of chemical pesticides and organic fertilizers

Type 3 was the smallest group compared to the other types, comprising about 16% of maize farmers surveyed. It differs from the other types in terms of access to agricultural credit, experience in maize cultivation and use of pesticides and organic fertilizers. It is characterized by relatively small farm size and area devoted to maize (10.4 and 6.2 are, respectively), low diversity of crops grown (2–3 on average) and about two crops associated with maize. They have easy access to agricultural credit (20.4%), investing it in the purchase of improved maize seeds (2%) and chemical pesticides (48.4%).

3.2.4 Type 4: Very well resourced and innovative farmers with large farm areas and large areas allocated to maize, access to agricultural credit and more income from maize farming

Type 4 represented ~ 16.7% of maize farmers. It is characterized by large farms (49.2 are on average), large areas devoted to maize (19.5 are on average) and high crop diversity (4 crops on average). Most farmers (21.99%) combine maize with other crops (2 crops on average). They have easy access to agricultural credit (23.6%) and derive a large part of their income from maize production. The adoption rate of improved varieties is higher (9.6%) than for other types, although they also use local varieties (11.4%). They also have higher rates of use of chemical fertilizers and pesticides than other types (10.4% and 51.6%, respectively).

3.3 Socio-economic factors and production constraints influencing maize-farm typologies in the South-Kivu province

Results from the univariate analysis show that age, education level, access to credit, and farming experience varied significantly among producers' clusters. However, no significant differences were observed between maize producer types for non-agricultural activities, contact with extension services and household size (Table 1).

3.3.1 Socio-economic factors and production constraints influencing belongingness to type 2 of maize farmers

The multinomial logistic regression model identified seven predictors as significant factors influencing whether farmers belong to type 2 maize producers. These predictors include five socio-economic factors and two constraints to maize production. They include the household head's gender, experience in maize production, having a non-agricultural activity, access to agricultural credit, income from maize production, lack of farm labor, and post-harvest losses (Table 4). Household head's experience in maize production (β = 0.07, p = 0.001) positively and significantly predicted farmers belongingness to type 2 maize producers compared to type 1. This implies that farmers with experience in maize production are likely to belong to type 2, especially since this group includes farmers with experience in maize production. Most of the farmers grow maize on small plots with limited access to resources (Table 3). This could explain the negative and significant prediction of access to agricultural credit (β = − 17.8, p < 0.0001), which was one of the discriminating parameters in the farmer typology. It means that farmers with limited access to agricultural credit tend to belong to type 2. Being poor in resources, farmers engage in non-agricultural activities to meet their livelihood needs.

Table 3 Characteristics of selected clusters of farmer households and constraints for maize production within each maize-farm type

Variables	Clusters				Cluster means ± SD	p-value
	Type 1 (40%)	Type 2 (27%)	Type 3 (16%)	Type 4 (16.7%)		
Variables using in maize-farm typology						
Farming experience	10.9 ± 0.62b	18.9 ± 1.9a	18.6 ± 2.3a	13.3 ± 1.4b	19.9 ± 6.1	< 0.0001
Landholding size	7.2 ± 0.9b	9.2 ± 0.8b	10.4 ± 1.1b	49.2 ± 11.4a	15.1	< 0.0001
Farm size	3.1 ± 0.3b	5.3 ± 0.4b	6.2 ± 0.7b	19.5 ± 5.9a	6. 9	< 0.0001
Crop diversity	3.1 ± 0.1b	1.6 ± 0.1c	1.6 ± 0.2c	3.5 ± 0.2a	2.5 ± 0.1	< 0.0001
Number of mixed crops	2.3 ± 0.1a	1.3 ± 0.1c	1.8 ± 0.2b	2.1 ± 0.1b	2.01 ± 0.8	< 0.0001
Cropping system						
Mixed cropping	30.9	9.4	10.5	22.0	72.8	< 0.0001
Sole cropping	0.5	13.01	9.9	3.7	27.2	
Off-farm activity						
No	22.5	14.7	9.9	13.6	60.7	0.07
Yes	8.9	7.8	10.5	12.0	39.3	
Access to credit						
No	31.4	22.5	0.0	2.1	56.0	< 0.0001
Yes	0.0	0.0	20.5	23.6	44.0	
Income from maize						
< 25%	12.0	5.8	3.1	9.9	30.9	0.002
25 to 49%	11.5	6.3	7.3	12.6	37.7	
50 to 75%	1.05	6.3	7.3	6.2	20.9	
˃ 75%	1.05	4.2	2.6	2.6	10.5	
Land ownership						
No	5.8	13.6	8.9	9.4	37.7	< 0.0001
Yes	25.6	8.9	11.5	16.2	62.3	
Type of maize variety used						
Local varieties	35.0	39.5	56.4	36.7	40.8	< 0.0001
IMVs	13.3	44.2	17.9	53.1	31.4	
Both local and IMV	51.7	16.3	25.6	10.2	27.7	
Use of chemical fertilizers						
No	30.9	22.0	20.4	15.2	88.5	< 0.0001
Yes	0.5	0.5	0.0	10.5	11.5	
Use of organic input						
No	1.0	10.5	4.7	1.0	17.3	< 0.0001
Yes	30.4	12.0	15.7	24.6	82.7	
Use of pesticides						
No	58.0	39.6	0.0	2.4	69.0	< 0.0001
Yes	0.0	0.0	48.4	51.6	31.0	
Contacts with extension services						
No	17.8	11.0	10.0	12.6	51.3	0.8
Yes	13.6	11.5	10.4	13.1	48.7	
Socio-economic characteristics and other maize farm attributes						
Age of household head	40.7 ± 1.7ab	44.3 ± 1.3a	41.4 ± 1.3ab	38.1 ± 1.7b	39.1 ± 3.2	0.032
Education level (years)	4.3 ± 0.4b	4.4 ± 0.5b	7.3 ± 0.6a	7.5 ± 0.6a	5.6 ± 1.4	< 0.0001
Household size	7.2 ± 0.3	5.4 ± 0.2	7.5 ± 0.5	5.1 ± 0.5	6.17 ± 3.11	0.537
Labor						
Family members only	10.0	10.0	3.1	0.5	23.6	< 0.0001
Family members and external labor	20.5	9.9	11.5	13.6	55.5	
External labor only	1.0	2.6	5.8	11.5	20.9	

Table 3 (continued)

Variables	Clusters				Cluster means ± SD	p-value
	Type 1 (40%)	Type 2 (27%)	Type 3 (16%)	Type 4 (16.7%)		
IMVSA						
Seeds are not available	18.3	13.1	13.6	16.7	61.8	0.75
Seeds are available	13.1	9.4	6.8	8.9	38.2	
Origin of seeds						
Recycling and friends	61.7	62.8	66.7	38.8	57.1	0.02
NGO and research center	38.3	37.2	33.3	61.2	42.9	
Field-house distance						
Near	16.2	7.3	5.2	7.8	36.6	0.03
Far	15.2	15.2	15.2	17.8	63.3	
Constraints for maize production (Constraint Severity Index)						
Disease constraint status						
Low	2.6	1.0	2.6	0.0	6.3	0.004
Medium	18.3	13.1	6.3	9.4	47.1	
High	10.5	8.4	11.5	16.2	46.6	
Low soil fertility						
Low	3.1	6.3	5.2	0.5	15.2	0.01
Medium	18.9	10.5	9.9	15.7	55.0	
High	9.4	5.8	5.2	9.4	29.8	
Lack of labor						
Low	3.3	4.6	17.9	0.0	5.8	< 0.0001
Medium	65.0	41.9	51.3	36.7	49.7	
High	31.7	53.5	30.8	63.3	44.5	
Lack of farmland						
Low	0.5	0.5	2.6	0.0	3.7	0.056
Medium	14.1	10.5	7.8	11.0	43.5	
High	16.7	11.5	9.9	14.7	52.9	
Quality seeds unavailability						
Low	2.6	1.0	2.6	0.0	6.3	0.004
Medium	18.3	13.1	6.3	9.4	47.1	
High	10.5	8.4	11.5	16.2	46.6	
Unavailability of farm inputs						
Low	4.7	5.8	3.7	0.0	14.1	< 0.0001
Medium	17.3	6.8	6.8	7.8	38.7	
High	9.4	9.9	9.9	17.8	47.1	
Lack of market demand						
Low	1.0	2.6	2.1	0.0	5.8	< 0.0001
Medium	27.7	11.5	13.1	10.5	62.8	
High	2.6	8.4	5.2	15.2	31.4	
Post-harvest losses						
Low	10.0	18.6	15.4	0.0	10.5	0.03
Medium	78.3	79.1	69.2	83.7	78.0	
High	11.7	2.3	15.4	16.3	11.5	
Tax hassles						
Low	7.3	11.0	12.6	20.9	51.8	< 0.0001
Medium	21.5	8.4	4.7	4.7	39.3	
High	2.6	3.1	3.1	0.0	8.9	

Table 3 (continued)

Variables	Clusters				Cluster means ± SD	p-value
	Type 1 (40%)	Type 2 (27%)	Type 3 (16%)	Type 4 (16.7%)		
Difficulty in weeding						
Low	6.3	6.8	3.1	0.0	16.2	< 0.0001
Medium	19.4	5.8	7.3	2.1	34.6	
High	5.8	9.9	9.9	23.6	49.2	

Farm constraints are presented as Constraint Severity Index (CSI). Difference in farmer type characteristics was detected with a one-way analysis of variance and HDS Turkey test at 5% probability level (for quantitative variables) and Khi^2 analysis test (for qualitative variables)

This would be explained as non-agricultural activities positively and significantly (β = 1.6, p = 0.001) predicted type 2 membership. Income from maize, in terms of contribution to total farm income, significantly and positively predicted type 2 membership (β = 0.48, p = 0.03). With an odd ratio greater than 1 (Fig. 5), income from maize significantly increased the probability of belonging to type 2 compared to types 1, 3 and 4. Finally, the gender of household heads negatively and significantly (β = − 1.11, p = 0.034) predicted farmers' type 2 membership. This signifies that female-headed households were more likely to belong to this type of farm than male-headed households. Regarding maize production constraints in the study area, it was observed that lack of farm labor significantly and positively predicted farmers' Type 2 membership (β = 0.89, p = 0.03, odd ratio = 2.43). This implies that lack of farm labor is the main production constraint for Type 2 farmers compared to Type 1, 3 and 4 farmers (Table 4, Fig. 5). On the other hand, post-harvest losses significantly and negatively

Fig. 5 Forest plot summarizing multinomial logistic regression models combining the contribution of multiple factors (socio-economic factors and maize production constraints) to maize farm typologies in South-Kivu province (types 2, 3 and 4) over only farm type 1. The x-axis shows odd ratios (OR) and Y-axis, factors
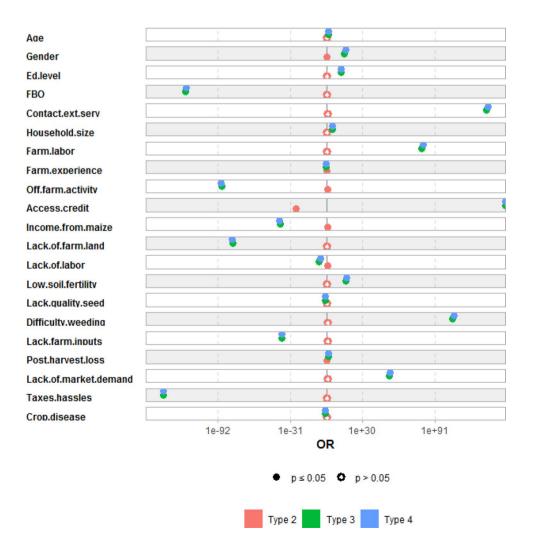
Table 4 Multinomial logistic regression (MNLR) of socioeconomic factors and maize production constraints influencing maize-farmers typologies (farm types 2, 3 and 4, over type 1, a reference modality)

Variables	Type 2		Type 3		Type 4	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constant	− 0.73	0.73	− 29.64	< 0.0001***	− 29.06	< 0.0001***
Age	− 0.01	0.39	2.86	< 0.0001***	− 2.82	< 0.0001***
Gender	− 1.11	0.03*	7.04	< 0.0001***	7.19	< 0.0001***
Education level	− 0.04	0.54	6.73	< 0.0001***	2.85	< 0.0001***
Membership of FBO	− 0.08	0.89	− 2.56	< 0.0001***	1.75	< 0.0001***
Contact with extension services	0.72	0.24	3.91	< 0.0001***	3.13	< 0.0001***
Household size	− 0.05	0.47	1.85	0.02*	4.19	0.001**
Farm labor	− 0.14	0.7	7.67	< 0.0001***	6.77	< 0.0001***
Farming experience	0.07	0.001**	0.36	0.09	− 1.89	0.001**
Off-farm activity	1.60	0.001**	− 189.36	< 0.0001***	− 18.71	< 0.0001***
Access To credit	− 1.78	< 0.0001***	5.62	< 0.0001***	5.38	< 0.0001***
Income from. maize	0.48	0.038*	− 1.66	< 0.0001***	− 8.19	< 0.0001***
Lack. of. farm land	− 0.41	0.32	− 9.74	< 0.0001***	− 9.88	< 0.0001***
Crop disease	− 0.07	0.71	− 5.29	< 0.0001***	− 6.06	< 0.0001***
Lack of labor	0.89	0.03*	− 1.55	0.06	0.56	0.48
Low soil fertility	− 0.46	0.21	3.33	< 0.0001***	3.28	< 0.0001***
Lack of quality seed	− 0.07	0.71	− 5.29	< 0.0001***	− 6.06	< 0.0001***
Difficulty in weeding	0.24	0.46	0.79	< 0.0001***	1.59	< 0.0001***
Lack of farm inputs	0.45	0.18	− 7.27	< 0.0001***	− 7.09	< 0.0001***
Post-harvest loss	− 1.04	0.03 *	− 5.55	< 0.0001***	− 5.68	< 0.0001***
Lack of market demand	0.63	0.19	1.26	< 0.0001***	2.71	< 0.0001***
Tax hassles	− 0.62	0.06	− 6.31	< 0.0001***	− 5.81	< 0.0001***

FBO farmer-based organization

*p < 0.05: significant, **(p < 0.01), and *** (p < 0.0001) highly significant

influenced the probability of belonging to this type for maize farmers (β = − 1.04, p = 0.03, odd ratio = 2.82). In other words, the more maize producers suffer losses, the less likely they are to be type 2.

3.3.2 Socio-economic factors and production constraints influencing membership to type 3 and type 4 of maize farmers

The MNLR results showed that belonging to Type 3 and Type 4 is explained by the same parameters, always related to Type 1, which is the reference group. We observed that the age of household heads, gender, level of education, membership of farmers' organizations, contact with extension services, household size, labor force, off-farm activities, access to credit and income from maize cultivation are the main factors explaining farmers' membership to types 3 and 4 maize producers. Furthermore, the production constraints that explain why farmers belong to type 3 are, among others, lack of arable land, crop diseases, low soil fertility, lack of quality seed, lack of agricultural inputs, post-harvest losses, lack of market and taxes. However, unlike type 3, the experience of household head also explained membership of type 4 compared to types 3 and 1.

Age significantly and positively predicted farmers' membership of both types 3 and 4 (β = 2.86, p < 0.0001 and β = 2.6, p < 0.0001, for types 3 and 4, respectively). This means that older farmers are more likely to belong to types 3 and 4 than younger farmers. For type 3, older farmers may be the most experienced in maize cultivation (β = 0.36, p = 0.09). While experience as household head negatively predicted belongingness to type 4 (β = − 1.89, p = 0.001), which groups farmers with little experience in maize production (Table 3). The gender and education level of the household head positively and significantly influenced the membership of farmers in types 3 and 4 (Table 4). Households headed by highly educated men are more likely to belong to these typologies than women and the least educated. In addition, the results showed that membership of a farmer organization significantly and negatively predicted type 3 membership (β = − 2.56, p ≤ 0.0001), while it positively predicted type 4 membership (β = 1.75, p < 0.0001). Contact with extension services, on

the other hand, positively predicted both types 3 and 4 membership ($\beta = 3.9$, $p < 0.0001$ and $\beta = 3.1$, $p < 0.0001$, respectively). This explains the high rate of adoption of agricultural innovations among type 4 farmers compared to others (Table 3). Household size also positively predicted Type 3 and Type 4 membership ($\beta = 1.85$, $p = 0.02$ and $\beta = 5.38$, $p = 0.001$, respectively) in the sense that farmers with many household members have a high probability of belonging to both types compared to small households. This would further explain the high availability of farm labor for these types of farmers using family labor. Access to credit has a positive and significant effect on types 3 and 4 membership ($\beta = 5.62$, $p < 0.0001$ and $\beta = 4.2$, $p < 0.0001$, respectively). While non-farm activities negatively affect the probability of belonging to both types (Table 4).

Regarding constraints to maize production, the MNLR shows that farmers belonging to types 3 and 4 face three major constraints. Among these are low soil fertility ($\beta = 3.3$, $p < 0.0001$ and $\beta = 3.2$, $p < 0.0001$, respectively), weed management ($\beta = 0.79$, $p < 0.0001$ and $\beta = 1.59$, $p < 0.0001$, respectively) and lack of market for their products ($\beta = 1.26$, $p < 0.0001$ and $\beta = 2.71$, $p < 0.0001$, respectively). The constraints positively and significantly predicted farmers' membership of the two types. The implication is that farmers facing these constraints are more likely to belong to types 3 and 4. This would explain the high rates of pesticide use in types 3 and 4 and chemical fertilizer use in type 4 (Table 3). Only one major constraint significantly explains why farmers belong to type 2. This was the lack of labor for agricultural activities.

3.4 Discussion

3.4.1 Maize-farm typology and patterns

This study aimed to develop a typology of maize producers among farmers in order to understand land ownership, land use patterns, characteristics of maize cultivation, cropping systems, agricultural innovations, socio-economic factors, and constraints related to maize production in different farm households in eastern DRC. Previous research has demonstrated that farm structure and functioning are key factors in differentiating farmers, and resources such as crops, and livestock contribute to categorizing farmers. Moreover, studies have highlighted that typologies can be based on other factors that explain farm functioning, depending on the specific objectives [23]. For instance, Musafiri et al. [45] characterized farming systems in Kenya according to their greenhouse gas production potential, while Priegnitz et al. [58] developed a typology of sweet potato farmers according to their adoption level of agricultural innovations, focusing specifically on attributes of the cropping system.

- Farm size and land use

  Total farm area and maize area were the key parameters in the typology of maize farmers in this study. Results showed a strong correlation between total farm area and maize area, suggesting a special emphasis on maize in the study area. This could be explained by the fact that maize is the main cereal grown and consumed in the area [40]. The results showed significant differences in the total farm area and the area allocated to maize between the farms types generated.

  The findings suggest a relationship between farm size and the area allocated to maize, indicating that smaller farms tend to allocate a larger proportion of their land to maize compared to larger farms. This trend may be attributed to a greater inclination for diversification among larger farms, leading them to allocate land to crops other than maize. This pattern was particularly evident in type 4 farms, characterized by high crop diversity and relatively low land allocation to maize. Another explanation could be the involvement of these farms in off-farm activities and their easier access to agricultural credit, enabling them to invest in diversification and on-farm innovations [69]. Given the significant importance of maize in the region, smallholder farms such as type 1 and type 2, which have limited access to resources, may prioritize allocating a larger portion of their land to maize cultivation to ensure their food security. This could be a strategic decision considering the reliance on maize as a staple crop in the area. The results corroborate those obtained by Kuivanen et al. [31], who found a negative correlation between farm size and area allocated to maize. In this context, agricultural intensification could lead to sustainable improvement in maize yields on these farms and meet their food needs.

- Farming experience

  Our results indicate that the level of farmers' experience in maize cultivation significantly differentiates the four types of maize farms, explaining their heterogeneity in South Kivu. According to Kumar et al. [32], farmers' experience is a key factor that determines their specific agricultural production and livelihood strategies. From our results, more experienced farmers tend to allocate more land to maize cultivation than less experienced farmers.

They also diversify their maize cropping systems, using monoculture and mixed cropping in almost equal proportions. The most common maize cropping system in the study area is intercropping. However, in some low-lying areas, maize is exclusively grown as monoculture, which would explain the distribution of this type of farmer in the Uvira area. These results corroborate those obtained by Yegbemey [5], who demonstrated that farming experience is positively and significantly correlated with the choice of land use strategies. According to these authors, farming experience positively influences the cropping system (association/rotation) and the redistribution of land within the farm. However, according to our results, these farms have a low crop diversity compared to types 1 and 4, with an average of 2 crops, among which maize is the main cereal, suggesting that they have a strong preference for maize. This may be explained with the fact that these farms, having tried several crops during their lifetime, specialize in a small number of crops for which they have mastered the technical itineraries and which are of great economic and nutritional importance to them, such as maize and cassava [15]. These findings are consistent with those of Altman et al. [2], who showed that young, and therefore less experienced, farmers tend to be more interested in diversifying their farms than more experienced farmers and tend to adopt crops other than tobacco in the USA. Although this type has a high rate of use of improved varieties compared to type 1 (less experienced), they have a low rate of adoption of agricultural innovations such as the use of chemical fertilizers and pesticides. This could be related to the low resource endowment of type 2 and 3 farmers. These results are in line with those of [11], who concluded that the resources of the farm or farm manager could condition the decision to adopt or not to adopt agricultural innovations, as they must finance them. On the other hand, contrary to our results and regardless of farm resources, [55] showed that farmers' experience positively influences the probability of adopting innovative technologies in India. Therefore, there is a need to organize technical training for less experienced farmers, as well as exchanges between experienced and less experienced farmers so they can learn from each other. Strong involvement from government agencies and NGOs should support this initiative.

- Income and uptake of agricultural innovations

Capital is a crucial element in the functioning of a farm, as it is needed to finance agricultural innovations and to cope with the various constraints faced by the farm [8, 13]. Capital can come from the farm manager's off-farm activities, but also from agricultural activities such as selling products or processing them by adding value [31]. It can also come from agricultural loans that the farm manager can obtain from financial structures [43, 49, 50]. The results of this study show that income from maize cultivation differs significantly between farm types. As a result, maize contributes more to total farm income for type 1 and 4 farmers than for type 2 and 3 farmers. For type 1, this could be explained by the fact that, being resource poor, they invest less, use local resources for soil fertilization, use family labor and market part of their production and make profits. There are significant differences between type 1 and 4, although maize contributed a lot to their income. This could be related to the fact that type 4 farmers have better access to agricultural credit, diversify their activities, have large areas and other sources of income, so they invest in the purchase of improved seeds and finance other agricultural innovations (chemical fertilizers and pesticides) to achieve high production. They are "business-oriented farmers" who are likely to market or process their production. These results are consistent with Makate et al. [37], which showed that innovative agricultural adoption is explained through access to key resources (credit, income and information), education levels and land holdings. Similarly, Cafer and Rikoon [8] found that money and capital, more than contact with extension services, influenced farmers' decisions to adopt packages of agricultural innovations in Ethiopia.

Results show that farm types adopt agricultural innovations differently. Type 4 adopted all four agricultural innovations, namely use of organic matter, use of improved varieties, use of chemical fertilizers and use of pesticides, which distinguishes it from the other types. Reasons for this could be their valuable resource endowment and income that can be reinvested to finance the different agricultural innovations [13]. In the other types, farmers adopted one of the packages of agricultural innovations. Type 3 adopted only the use of pesticides and improved varieties, while type 2 adopted only the use of improved varieties and type 1 adopted only the use of organic matter. This is explained by lack of financial capital to purchase improved and quality seed, pesticides, and chemical fertilizer [30]. The high use of organic matter by all types of maize farmers may be related to the fact that most farmers have at least one livestock unit, which is an important source of organic manure in integrated farming and livestock systems [35] . These results are consistent with Priegnitz et al. [58], who developed a farmer typology based on adoption of agricultural innovations in sweet potato farming. The authors showed that variety adoption improved sweet potato yields more than pesticide adoption, depending on the farm's financial resources.

3.4.2 Socio-economic factors influencing the maize famer's typologies

The multinomial logistic regression (MNLR) results showed that head's experience, access to agricultural credit, off-farm activities, maize income, and head's gender significantly influenced whether farmers belonged to type 2. While age of household head, gender, level of education, membership in farmer organizations, contact with extension services, household size, labor force, off-farm activities, access to credit and income from maize cultivation significantly explained whether farmers belonged to type 3 and 4 compared to type 1.

The positive influence of farming experience would be explained by the fact that type 2 is represented by the oldest farmers (≥ 45 years) compared to type 1. They are traditional farmers, less likely to adopt agricultural innovations and resource poor. There is a direct relationship between the age of the household head and farming experience [6] as well as the adoption of agricultural innovations [32]. Regarding adoption of innovations, our findings indicate that Type 4, which represents young, thus less experienced farmers, adopted all agricultural innovations. In fact, younger farmers are more likely to be flexible than older farmers and therefore more likely to adopt innovative technology. In contrast, other studies have elucidated the positive influence of experience on the adoption of agricultural innovations [55]. Type 2 is marked by low access to agricultural credit and strong involvement of farmers in off-farm activities. These farmers could explain this need to meet their daily needs due to lack of access to agricultural credit. Similarly, Yegbemey [5] and Sarker et al. [38] show that farmers assume off-farm activities to diversify their sources of income and become more resilient to the hazards in their lives. According to our results, gender negatively predicted type 2 membership. This suggests that these farms are more likely to be owned by women than by men. One explanation for this could be that in the region, most resources are held by men, be it land or other assets, and women are second in decision making within the farm.

The level of education positively and significantly determined whether a farmer belonged to type 3 or type 4. These are farmers who have adopted certain agricultural innovations: using plant protection products, using organic fertilizers, using chemical fertilizers, using improved varieties. It may also reflect that highly educated farmers quickly understand the benefits of agricultural innovations and tend to take advantage of these innovations in comparison to less educated farmers. This also explains the high adoption rate observed for type 4. These results are consistent with those of Makate et al. [37], who found that in rural areas, the number of agricultural innovations adopted increases as farmers' education increases. In addition, these results explain the positive influence of membership in farmer organizations and contact with extension services in predicting type 3 and 4 adoption by farmers. Membership of agricultural organizations and contact with extension services are important sources of information which facilitate the exposure of farmers to agricultural innovations and promote their uptake [61]. Within the farmer organization, farmers receive multiple trainings on farming practices and crop management, develop agricultural cooperatives to better market their products, and are motivated to make good technology choices [5]. Household size and labor force positively predicted type 3 and type 4 farmers' membership. This may reflect the fact that most farm households (type 3 and 4) use family workers for various farm tasks. Furthermore, according to [3, 4], larger households have an abundance of labor available for on-farm or off-farm activities. Labor availability has also been shown to guide land use decisions and increase farm productivity [55], which explains why farmers belong to type 4.

3.4.3 Constraints for maize production in farm typologies and interventions

Lack of farm labor was a major constraint to maize production for Type 2 farmers. According to the results, most type 2 farmers (20%) rely on family and external labor to conduct farm work. Therefore, they noted a shortage of farm labor, which is a major constraint for them. Labor is a crucial factor of production on a farm [18]. The shortage of labor observed among type 2 farmers is explained by the phenomenon of rural exodus of young people and the abandonment of agricultural activities in some rural areas of South Kivu, which significantly reduces the number of workers in households, with a significant impact on productivity [53]. To meet the demand for labor, farmers rely on external labor from neighboring countries such as Rwanda and Burundi. This has a significant impact on the technical efficiency of the farm and the cost of production [41]. Cafer and Rikoon [8], Kumar et al. [32] found that labor availability is an important determinant of farm heterogeneity and a facilitator in the adoption process of agricultural innovations. To solve the problem of labor shortage and its impact on the technical efficiency and productivity of type 1 and 2 farms, it would be better to first develop the necessary strategies to limit the rural exodus and thus maintain the availability of labor in rural areas [34]. In the Uvira area, initiating agricultural projects aimed at encouraging young people to work more in the agricultural sector would be a better way to raise farmers' awareness of the need to work in the fields. Another way to deal with the labor shortage would be to increase the productivity of the existing labor force by gradually integrating mechanization into the

farms. The two approaches are complementary, as investment costs can be reduced by substituting farm machinery for the missing labor [21]. Obviously, the topography of the area under consideration and its location must be considered.

Declining soil fertility has been identified as one of the main constraints to maize production on type 3 and 4 farm types and determines whether farmers belong to these farm types. Regardless of the number of NGOs working in these areas, this decline in soil fertility is explained by the poor dissemination and application of soil fertility management practices on farms, such as the burial of crop residues, mineral fertilization under the Integrated Soil Fertility Management (ISFM) approach, the use of green manures, the use of biofertilizers, etc. [52]. Studies have shown that soil fertility is a key factor as it conditioned the growth and development of crops and determines their yield [9]. Soil degradation manifests itself through degradation of physical, chemical, and biological properties, causing significant loss of essential soil nutrients required for crop growth [64]. An important means of increasing crop yields would be to develop techniques to improve soil and restore soil fertility in agricultural areas. Ecologically sustainable techniques such as those proposed by conservation agriculture, such as ISFM, adding organic matter, burying crop debris, green manuring, fallow, and so on, are important [63]. Besides these techniques, integrating legumes into cropping systems is also essential to increase soil fertility [39]. Many farmers around the world have also adopted other techniques based on using biofertilizers [36, 49, 51, 52]. The most important of these are fungi and rhizosphere or endophytic bacteria [17, 48, 66, 70]. Using maize genotypes with high nutrient use efficiency would also be a better option to significantly reduce the amount of fertilizer needed, the cost of which is often unaffordable for resource-poor smallholders like those in Types 1 and 2. To increase the use of mineral fertilizers under the ISFM approach, it is necessary to disseminate them to farmers to increase the adoption rate. However, as the cost of these fertilizers is higher than the purchasing power of farmers, the government should consider subsidizing them to reduce the burden on farmers.

The MNLR showed that lack of market significantly and positively predicted type 3 and 4 farmer membership compared to type 1. This could be related to the fact that most maize farmers' fields are located far from the Centre's of product disposal (markets). In addition, the poor condition of rural roads makes it difficult to sell products in major consumption centres such as Bukavu or Uvira town. Furthermore, farmers do not have enough resources to add value to their products to attract more buyers and be more competitive in the market [28, 47]. The lack of a market for agricultural products leads to huge losses in production, either due to the deterioration of the product or price discounting by producers to avoid huge losses [14]. This will help farmers to overcome various production constraints. To facilitate contacts between producers and potential buyers, structures should be set up in the main production centres. These structures should be able to monitor the market and identify potential buyers in the main consumption centres, thus facilitating the sale of products. This could also be done by developing start-ups and creating digital marketplaces using modern technologies or telephonic applications, which can link all actors in the agricultural sector or value chain, thus facilitating the marketing of products. These technologies can also facilitate the dissemination of information and the adoption of agricultural innovations on farms [1,5].

4 Conclusion

The maize farm typology developed in this study successfully categorized maize farms into four distinct types based on 15 variables related to their structure and functioning. The study provides a better understanding of the different categories of maize producers in South- Kivu, allowing for the design of interventions that are better tailored to the specific needs of each group. For example, producers who are better endowed with resources can benefit from advanced production technologies, while those with fewer resources can receive assistance to improve access to inputs and credit. By considering the specific preferences and constraints of maize producers, it becomes possible to more effectively promote agricultural innovations. Maize varieties and agricultural practices introduced are likely to be better accepted if they address the needs of the distinct categories of producers. Policymakers can use the study's results to develop more targeted and equitable agricultural policies. This includes improving access to land and credit for small producers, promoting the use of mineral and bio-fertilizers, and implementing support mechanisms for the most vulnerable producers. Improving rural infrastructure such as roads, markets, and storage facilities can be planned more strategically, with particular attention to areas where the neediest producers are located. This will facilitate market access and increase the value added to agricultural products. Implementing a monitoring and evaluation system based on producer typologies will allow for measuring the impact of interventions and adjusting strategies based on the results obtained and feedback from producers.

To gain a more comprehensive understanding of the complexity of farms, it would be beneficial to involve farmers and incorporate their perspectives in the implementation of the farm typology. Furthermore, it would be valuable to examine the geographical distribution of the different farm types across the South-Kivu to better locate and plan interventions in specific areas.

5 Policy implications of the study

The adoption of agricultural innovations and the alleviation of production constraints in maize cultivation are key drivers to ensure effective agricultural improvement in South-Kivu. This entails a precise, efficient, and objective targeting of beneficiaries for initiatives led by decision-makers and non-governmental organizations operating in the Kivu region, often spearheading development projects in the DRC, particularly in South-Kivu. Identifying target groups for the dissemination of agricultural innovations must consider socio-economic parameters and farm structures to enhance adoption prospects. This requires classifying farms into distinct categories to differentiate them effectively.

The findings of this study highlight the value of utilizing farm typology as a decision-making tool to gain insights into the specific characteristics and constraints faced by different groups of maize farmers. Moreover, the typology approach can guide targeted interventions aimed at addressing the identified constraints and maximizing the impact of interventions in the maize farming sector. The results of the typology of farmers indicate the existence of four classes of maize producers, differentiated by their socio-economic characteristics and structure. Interventions in rural areas should therefore consider this typology to enhance their effectiveness. For example, farms of types 3 and 4, being better endowed with resources and facing fewer constraints, should focus interventions on optimizing production techniques and innovation to increase productivity and sustainability, as compared to those of types 1 and 2. Consequently, different approaches should be considered according to the identified categories based on their specific resources and constraints. From an institutional perspective, the following measures and decisions should be considered:

- Given that farm size is one of the factors differentiating type 1 and 2 farms from those of types 3 and 4, due to their resource-poor status, developing a policy to increase access to land and agricultural credit for these types of producers would be a crucial lever to boost maize production in South Kivu. It has been reported that agricultural soils in South Kivu are at an advanced stage of degradation due to soil erosion, leading to the loss of fertility in most agricultural soils [22]. It is therefore imperative to promote sustainable land management techniques by disseminating integrated soil fertility management (ISFM) practices. In the context of land scarcity and low productivity, agricultural intensification remains the most promising way to sustainably improve soil fertility and increase maize productivity across all identified types of producers. Particularly for type 1, improving the adoption of agricultural innovations should be considered, as this class consists of non-adopters. Indeed, the strategies for types 1, 2, and 3 maize producers should first focus on improving access to resources (e.g., credits) to enhance their capacity to acquire agricultural innovations. It is essential to facilitate access to financing for maize producers, particularly for those of types 1 and 2, by establishing microcredit mechanisms and targeted subsidies. Financial institutions should also be encouraged to develop financial products tailored to the needs of the different types of producers. Secondly, it is crucial to develop and disseminate new maize varieties that consider farmers' preferences to enhance their adoption. The lack of consideration for farmers' preferences has negatively impacted the adoption of several maize varieties disseminated in South Kivu [49, 50]. Structuring the seed system is another solution to consider, as it would improve the supply and quality of maize seeds in South Kivu, reduce seed prices, and enhance accessibility for the most disadvantaged producers. This approach would subsequently improve the adoption rates of improved maize varieties [42].
- The rate of mineral fertilizer use remains very low in sub-Saharan Africa, particularly in the DRC. However, it is well established that mineral fertilizers provide essential nutrients and increase crop yields (). It is important to promote the use of mineral fertilizers in type 1 and 2 farms, in combination with other sustainable soil fertility management techniques, as previously described. Policymakers should consider the subsidy of mineral fertilizers, capacity building for farmers on the use of fertilizers, sustainable soil management techniques, and the promotion of biofertilizers.
- Improving access to information would enhance the adoption of agricultural innovations. Restructuring extension services is essential for boosting the adoption of agricultural innovations and improving access to these innovations. Other initiatives include organizing agricultural innovation fairs (e.g., seed fairs), dissemination campaigns, and establishing input supply shops (for seeds, fertilizers, etc.).

- Improving market access is crucial for small farms of types 1 and 2 to add value to their products. In this context, enhancing rural infrastructure such as roads, markets, and product quality is paramount, with particular attention given to areas where producers of types 1 and 2 are located.

Considering the typology of maize producers, these policy measures aim to enhance the effectiveness of agricultural interventions, promote the adoption of innovations, and mitigate production constraints. Differentiated and targeted approaches will facilitate achieving these objectives more efficiently and equitably. Subsequently, a monitoring and evaluation system should be established to assess the impact of policies and interventions on each type of producer. It is also crucial to adjust policies and interventions based on the outcomes obtained and feedback from producers.

Data availability Raw and treated data generated during study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate The Interdisciplinary Centre of Ethical Research (CIRE) of the Université Evangélique en Afrique (UEA), Ref, approved the study protocol: CNES 008/DPSK/118PP/2022. We obtained consent from all resource-persons and households prior focus group discussions and data collection after ensuring the participants of the confidentiality in use of data collected.

Consent for publication The data in the manuscript have been agreed upon by all of us, and we have submitted our final manuscript to the Journal of Discover Agriculture.

Competing interests The authors declare that they have no competing interests.

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