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Characterization and adoption of sustainable intensification practices in maize (*Zea mays* L.) production systems in South Kivu, DR Congo

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Abstract

Maize farming plays a central role in food security and household income in South Kivu. However, the process of intensification of this agro-ecosystem remains poorly studied in the agro-ecological zones of South Kivu. Therefore, which intensive agricultural practices are adopted within maize farms in South Kivu, and how are these practices influenced by farm characteristics and distribution? This study aimed to characterize maize farms based on their level of intensification, to evaluate their distribution and to identify the socio-economic factors influencing the adoption of intensive agricultural practices. A quantitative survey was conducted among 287 farmers distributed across Kabare (91), Walungu (100), and Uvira (96). Data were analyzed using Principal Component Analysis (PCA) and Hierarchical Cluster Analysis (HCA) to establish the typology, completed by logistic regression to estimate the determinants of adoption. Four types of maize farms were identified: low-intensive farms, large farms with moderate adoption, diversified farms with partial adoption, and highly intensive farms. Low-intensive farms (43.5%) are generally small-scale, with an average size of 1.69 ± 0.68 ha. Large farms with moderate adoption (12.7%) are characterized by relatively good access to credit (83.3%) and partial use of chemical fertilizers (52.8%). Diversified farms with partial adoption (33.9%) combine mixed cropping systems with the use of organic fertilizers (44.8%). Finally, highly intensive farms (9.9%) are larger on average (3.79 ha) and are mainly specialized in maize production. Spatially, Kabare shows the highest proportion of intensive farms ($\approx 45\text{--}50\%$), followed by Walungu ($\approx 35\text{--}40\%$), while Uvira was dominated by low-intensity farms ($> 60\%$). The use of chemical fertilizers remains low (Kabare 15.6%, Walungu 10%, Uvira 0%), whereas organic fertilization is widely practiced (Kabare 98.9%, Walungu 89%, Uvira 46.2%). Regression results indicate that access to credit ($OR = 3.27$; $p = 0.021$), household size ($OR = 2.45$; $p = 0.038$), farming experience ($OR = 1.89$; $p = 0.044$), and income derived from maize ($OR = 3.96$; $p = 0.035$) positively influence the adoption of intensive practices. Maize farming systems in South Kivu show strong heterogeneity in the adoption of intensive agricultural practices across farm types and territories. Strengthening access to credit, inputs, and extension



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services is essential to enhance the adoption of these practices and promote sustainable intensification in the region.

Keywords Maize production systems, Farm typology, Adoption, Socio-economic factors, South Kivu, Sustainable intensification

1 Introduction

Agriculture remains a vital sector for global food security, particularly in developing regions, where it constitutes one of the primary livelihoods for rural populations [39]. Globally, maize (*Zea mays* L.) occupies a strategic position within agri-food systems due to its role in food security and its contribution to household incomes [3]. It is the most widely produced cereal in the world, exhibiting broad adaptation to diverse agroecological conditions and an increasing significance in national agricultural policies [16].

In sub-Saharan Africa, maize is the principal staple cereal, cultivated both for subsistence and for sale [20]. Despite its importance, productivity remains very low, with average yields far below those observed in industrialized countries [45]. In the Democratic Republic of Congo (DRC), over 70% of the population relies on agriculture for survival [40], and maize is among the most widely cultivated crops at the national level [36]. This cereal represents a major source of food and income for millions of households, particularly in the eastern regions of the country, where land tenure insecurity and climatic disruptions exacerbate the vulnerability of agricultural systems [32]. In South Kivu Province, maize is cultivated across nearly all territories [30]. It holds a prominent place in daily household diets and also serves as a cash crop [31]. However, yields remain very low, averaging around 800 kg ha⁻¹, whereas agronomic potentials exceed 3 tonnes [58].

The low productivity of maize on agricultural farms can largely be attributed to the constraints faced by farmers, notably soil degradation, which is associated with a drastic decline in soil fertility, limited adoption of agricultural innovations, and scarce resources such as land, fertilizers and adapted seed, and capital [26, 36]. In addition, the scarcity of arable land, exacerbated by increasing rural population pressure, further limits production [33]. This scarcity results in smaller farm sizes and intensive land use, often without soil regeneration practices. The absence of fallow periods and the continuous cultivation of the same plots accelerate the degradation of land quality [41]. Consequently, limited access to land constitutes a major barrier to improving productivity and adopting sustainable agricultural practices [6]. Beyond these constraints, the heterogeneity of farmers' socio-economic profiles, the diversity of agricultural practices employed, and the availability of production resources also contribute to the persistently low agricultural output in rural areas of South Kivu.

Indeed, agricultural farms do not constitute a homogeneous group; they differ according to economic, social, technical, and environmental criteria [54]. Some farmers adopt intensive practices, combining modern inputs, increased crop density, and reduced fallow periods, while others maintain more traditional extensive practices [36, 38]. This heterogeneity complicates the design of appropriate agricultural policies and targeted technical support [24, 55]. In this context, intensive agriculture could provide a solution for sustainable soil management and improved maize productivity [22]. A study conducted by Laub et al. [29] in Kenya demonstrated that integrating organic manure with mineral fertilizers increased maize yields on small farms. Similarly, the adoption of

maize-legume rotation not only partially restored soil fertility but also enhanced overall productivity without the need for costly inputs.

Among intensive agricultural practices, the adoption of improved maize varieties represents a key strategy for enhancing crop productivity. These varieties, often selected for their high yield potential, drought tolerance, or disease resistance, optimize soil use while reducing losses due to biotic and abiotic stresses [46]. Additionally, the combined application of organic and mineral fertilizers constitutes an important lever for restoring or maintaining soil fertility while supporting productivity [2]. Chivenge et al. [10] demonstrated that integrated fertilization not only increases maize root and shoot biomass but also improves soil organic matter content, nitrogen availability, and soil structure, resulting in yield increases exceeding 60%. The judicious use of agrochemicals complements this strategy by protecting crops against pests and diseases, thereby limiting yield losses. Therefore, a typology of maize farmers based on reliable empirical data would not only improve the understanding of local agricultural decision-making but also allow for the classification of farmers into homogeneous groups for targeted interventions [35]. This approach is particularly important in a context like South Kivu, characterized by fragmented land holdings, diverse agricultural practices, and the coexistence of both extensive and intensive farming systems that remain poorly documented.

Furthermore, it is essential to identify the locally implemented intensive agricultural practices and the factors influencing their adoption [36]. Numerous studies have shown that the adoption of agricultural innovations is largely determined by farmers' socio-economic characteristics and their environmental context [43]. Nevertheless, few studies have concurrently examined farm diversity and intensive farming practices, particularly for maize, which remains a staple crop with a critical role in food security. Understanding the heterogeneity of farms and the adoption patterns of intensive practices is therefore crucial for designing targeted interventions and promoting sustainable productivity gains. This study aims to address this gap by providing a structured analysis of the diversity of maize producers in South Kivu and the intensive agricultural practices they implement, with the ultimate goal of enhancing maize productivity and supporting food security in the region. This study addresses four research questions: (i) what are the main typologies of maize farmers based on their socio-economic characteristics and crop-management practices in South Kivu; (ii) how are these farmer typologies distributed across Kabare, Walungu, and Uvira; (iii) which sustainable intensification practices are adopted within each typology; and (iv) which socio-economic, institutional, and agronomic factors influence the adoption of these practices? Addressing these questions is beneficial for farmers because it helps identify technically feasible and economically accessible intensification pathways, and it is useful for decision-makers because it provides an empirical basis for targeting credit, extension, input-supply, and soil-fertility interventions according to farm type and territory. Therefore, this study aims to: (i) characterize the different typologies of maize farmers based on their socio-economic attributes and crop management practices in South Kivu, (ii) map the distribution of these farmer typologies across the various territories of the province, (iii) identify the intensive agricultural practices implemented by farmers according to the identified categories, and (iv) determine the factors influencing the adoption of these practices within the different farmer groups.

2 Conceptual framework

2.1 Agricultural intensification

Agricultural intensification refers to the process through which farmers increase agricultural output per unit of land by improving input-use efficiency and adopting enhanced production technologies. In contemporary literature, this process is increasingly framed as sustainable crop production intensification, which aims to increase productivity while safeguarding the ecological, social, and economic foundations of farming systems [18, 47].

Sustainable intensification practices include technological and agronomic innovations such as improved and hybrid seeds, mineral fertilizers and organic amendments, integrated soil fertility management (ISFM), conservation agriculture, crop rotation, intercropping, irrigation and water-harvesting systems, integrated pest and disease management, agroforestry practices, and appropriate mechanization [18, 47, 55]. However, the level and pathway of intensification vary widely across farming systems because farmers differ in resource endowment, labour availability, land tenure, market access, and agroecological conditions. In many smallholder contexts of sub-Saharan Africa, structural constraints such as limited fertilizer access, weak input markets, land degradation, and climate variability lead farmers to adopt partial or combined strategies rather than complete technological packages [2, 22].

2.2 Adoption of intensive agricultural practices

The adoption of intensive agricultural practices is a central lever in the transformation of agricultural systems, particularly in smallholder farming contexts where the sustainable increase in productivity is a priority. It refers to the process through which farmers decide to integrate, use, and maintain technological innovations aimed at increasing agricultural output per unit of land. This adoption is now conceptualized as a dynamic, gradual, and heterogeneous process, influenced by farmers' characteristics, structural constraints, and agro-ecological conditions [49].

Intensive agricultural practices encompass a set of technologies and crop management strategies, including the use of improved and hybrid seeds, application of mineral and organic fertilizers, integrated soil fertility management systems, soil conservation techniques (crop rotation, mulching, reduced tillage), irrigation and water management, as well as integrated pest and disease management. In some agricultural systems, mechanization and precision agriculture also represent advanced forms of intensification. Recent studies show that these practices are often adopted in a partial and combined manner rather than as a complete technological package [47, 49]. The adoption of these practices is determined by a set of multidimensional factors. Socio-economic factors include age, education level, farming experience, household size, and income, which influence farmers' ability to access information and make rational risk-based decisions. Several recent studies confirm that education and gender remain key determinants of both the speed and intensity of agricultural innovation adoption [43]. Resource-related factors also play a crucial role. Farm size, land tenure security, labor availability, and access to credit directly determine farmers' capacity to invest in intensive inputs and technologies. In addition, institutional factors such as access to agricultural extension services, participation in farmer organizations, access to subsidized inputs, and technical training significantly increase the likelihood of adoption [34]. Agro-ecological factors also

strongly influence adoption decisions. Soil fertility, climate variability, water availability, and topography determine the suitability and profitability of intensive practices. Recent findings show that climate constraints reduce yield stability and increase uncertainty, thereby negatively affecting adoption in some vulnerable regions [5].

Adoption is generally measured through several complementary dimensions. It can be assessed in binary terms (adopter/non-adopter), but this approach is now considered insufficient. More robust indicators include adoption rate, adoption intensity (quantity of inputs used per hectare), composite adoption indices (measuring the simultaneous integration of multiple practices), and continuity of adoption over time. These measures better capture the reality of agricultural systems where adoption is often partial and progressive [49]. Finally, it is important to highlight that adoption varies significantly across farmer typologies. Farmers with greater resources and better market integration tend to adopt innovations more quickly and more intensively, whereas small-scale farmers face structural constraints that limit their adoption capacity. Thus, adoption constitutes the central mechanism linking farmer characteristics to agricultural intensification outcomes and overall production system performance. This study adopts a systems-based approach to agricultural intensification, focusing on the characterization of maize farmer typologies and the determinants of adoption of sustainable intensification practices in maize (*Zea mays* L.) production systems across territories in South Kivu, DR Congo.

Figure 1 illustrates the analytical pathway adopted in several studies [9, 28, 48] to investigate sustainable agricultural intensification (SAI) in farming systems. It begins with the 1) explanatory (independent) variables, including farmers' socio-economic characteristics, farm resource endowment, institutional and market factors, and agro-ecological and contextual conditions, which collectively influence farmers' production decisions (1). These characteristics are used to classify farmers into distinct typologies (latent classes) sharing similar socioeconomic and production attributes. The framework further considers the spatial distribution of these typologies across the study territories, highlighting territorial heterogeneity in farming systems and resource availability (2). Each farmer typology is then characterized according to its adoption of sustainable agricultural intensification practices, with adoption levels assessed for individual practices (3). Subsequently, the framework identifies the determinants of adoption by examining

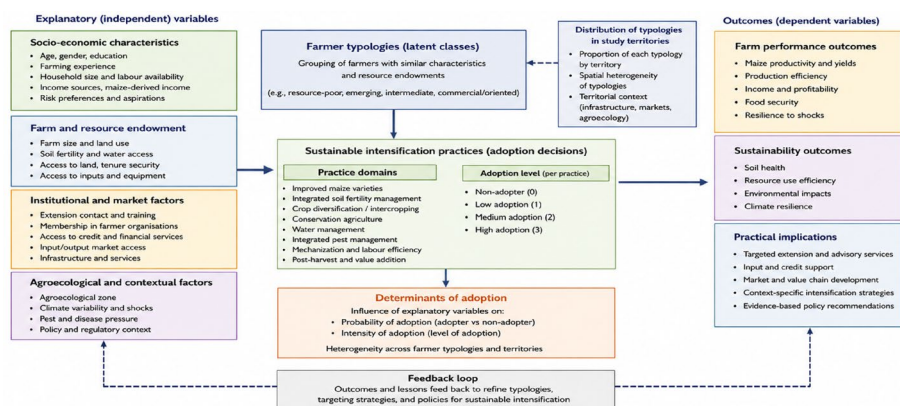


Fig. 1 Conceptual framework: identification of sustainable agricultural intensification practices across farmer typologies, assessment of adoption levels, spatial distribution of typologies across study territories, and the determinants of practice adoption in maize-based farming systems

how the explanatory variables affect both the probability and intensity of practice adoption across farmer typologies and territories (4). Finally, the observed adoption patterns provide insights into farm performance and sustainability outcomes, generating evidence to support context-specific extension services, agricultural interventions, and policy recommendations aimed at promoting sustainable maize production.

3 Materials and methods

3.1 Field site description

The study was conducted in South Kivu Province, located in the eastern part of the Democratic Republic of the Congo (DRC). Three territories were targeted: Kabare, Walungu, and Uvira (Fig. 2), selected for their importance in maize cultivation, agroecological diversity, and logistical accessibility [36]. To ensure consistency, all geographic coordinates are presented in decimal-degree format. Kabare is located approximately between 2.50° and 2.83° S and between 28.75° and 28.92° E, with elevations ranging from 1,460 to 3,000 m. The climate is humid tropical, with an average annual rainfall of approximately 1,600 mm and a mean monthly temperature of 19.67 ± 2.3 °C [11]. Walungu lies approximately between 2.62° and 2.69° S and between 28.41° and 28.76° E, at elevations ranging from 1,000 to 3,000 m. It receives rainfall comparable to Kabare but exhibits greater thermal variability. Uvira is situated in a lower-altitude zone, approximately between 3.33° and 4.33° S and between 29.00° and 29.30° E, with elevations of about 800–900 m and a semi-arid climate characterized by maximum monthly temperatures reaching up to 32 °C [36]. All three sites experience a bimodal climatic pattern with two main cropping seasons, from mid-September to mid-January and from mid-February to mid-June [13], which provides suitable conditions for studying maize production and sustainable intensification practices.

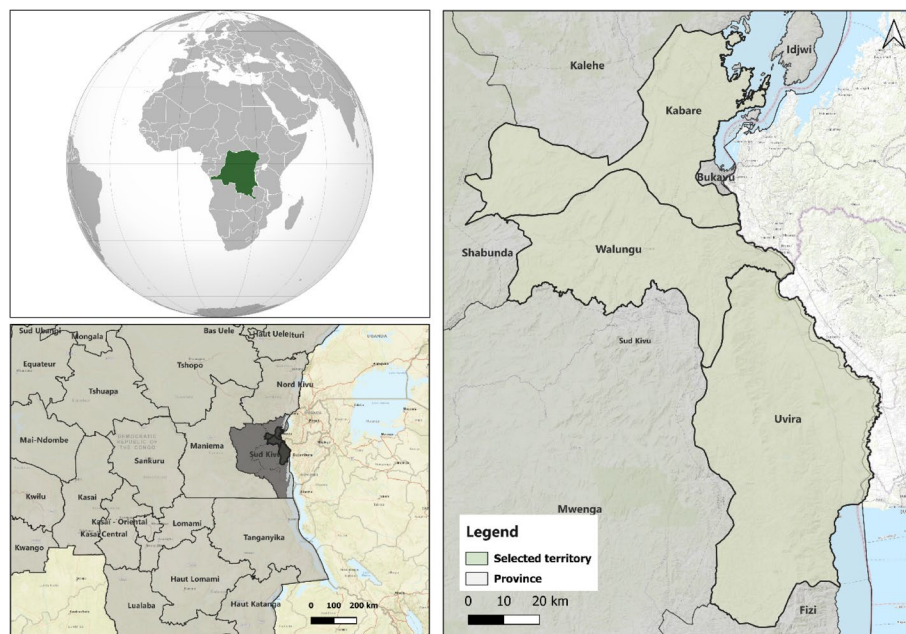


Fig. 2 Map of the South-Kivu province showing selected sites (Kabare, Walungu, and Uvira territories) of the study area

3.2 Household survey and data collection

A stratified random sampling method, as reported by Amare et al. [4] and Saha et al. [42], was employed to ensure adequate representativeness of maize producers across the three study territories (Kabare, Walungu, and Uvira). Each territory was treated as a distinct geographic stratum. Within each stratum, localities (villages or administrative clusters) were randomly selected as primary sampling units, followed by the random selection of maize-producing households within each locality. Empirical data were collected using a semi-structured questionnaire programmed in the KoboCollect application. The questionnaire comprised multiple types of items designed to gather diverse and accurate information. These included closed-ended questions, such as yes/no responses, multiple-choice items, and numerical entries. Additionally, semi-open questions were used to allow for brief but more detailed responses. Finally, Likert-scale items (ranging from 1 to 5) were included to assess farmers' perceptions of various constraints affecting maize production.

To address the objectives of this study, the methodology begins with the collection of representative primary data from maize producers across the three study territories. These data was used to characterize homogeneous groups of producers (typologies) based on their technical, structural, and socio-economic profiles; to analyze their spatial distribution within the study areas (mapping); to identify the intensive agricultural practices implemented within each typology; and subsequently to assess the factors influencing their adoption.

3.2.1 Characterization of maize producer typologies in South Kivu

To characterize the different types of maize producers in South Kivu, we adopted a multivariate statistical approach inspired by the methodologies of Chikowo et al. [9], Titttonell et al. [52], and Ndeko et al. [36]. This multivariate procedure consisted of two main steps: Principal Component Analysis (PCA) and Hierarchical Cluster Analysis (HCA). PCA is a multidimensional analysis technique that reduces a large set of variables into a smaller number of components while retaining most of the original information. It facilitates the identification of relationships among variables and reveals hidden structural patterns within farming systems. The selected groups of variables used in this analysis included socio-economic characteristics of the farmers, agronomic characteristics, resource availability, and production constraints. To evaluate the suitability of PCA, two tests were conducted: the Bartlett sphericity test and the Kaiser-Meier-Olkin (KMO) test [36]. Kaiser's "absolute" criterion was applied, retaining all factors (components) with eigenvalues greater than 1. The second step consisted of applying HCA to the factorial coordinates derived from the PCA to group farms with similar characteristics. This clustering method, based on Ward's algorithm, progressively forms homogeneous groups. The optimal number of clusters was determined through examination of the resulting dendrogram. Interpretation of the identified clusters enabled the delineation of distinct typologies of maize producers in South Kivu according to their farming practices, productive resources, and degree of agricultural intensification.

3.2.2 Mapping of maize farmer typologies across the territories

Data collected from the producer survey were complemented with the geographic coordinates of each farm in order to ensure accurate geolocation, as reported. The typologies

derived from the multivariate analysis and clustering procedures (previous objective) were integrated into a Geographic Information System (GIS) using ArcGIS 10.4. The spatial representation was produced through point maps colored according to typology, as well as choropleth and density maps to identify areas of high concentration, following the approach of Lafevor [28]. Administrative boundaries were added to facilitate spatial interpretation in accordance with standard practices in geographic visualization.

3.2.3 Identification of intensive agricultural practices implemented by maize producers

The identification of intensive agricultural practices in maize production in South Kivu followed the framework proposed by several authors, including Titttonell and Giller [51], Vanlauwe et al. [55], and the FAO [19], who define intensification as a combination of the rational use of external inputs and the efficient mobilization of local resources. Based on this approach, several agricultural practices were selected to characterize the degree of intensification among maize farms. These practices include organic soil fertilization (application of manure, compost, and crop residues), mineral fertilization (such as urea and NPK), the adoption of improved maize seeds, and plant protection using chemical pesticides or biopesticides to control pests and diseases. In addition to these practices, labor management was also considered a key component of intensification, particularly the combined use of family and hired labor to strengthen crop management operations. Furthermore, cropping systems based on maize–legume intercropping, agricultural mechanization, and crop rotation were included, as they contribute to sustainable production. These different practices were recorded and coded in binary form (1 for adoption and 0 for non-adoption) in order to assess their level of diffusion and to evaluate their impact on the performance of the surveyed farms within the study area.

3.2.4 Identification of factors determining the adoption of intensive agricultural practices

The study further investigates the determinants of the adoption of intensive agricultural practices among maize producers in South Kivu using a quantitative analytical approach aimed at assessing the influence of individual, economic, social, and territorial factors. The objective was to explain why certain farmers adopt intensive agricultural practices more readily than others, even under similar agroecological conditions. Some intensive agricultural practices, including the use of chemical fertilizers, the use of organic fertilizers, and cropping system diversification, were analyzed independently as binary dependent variables (1 = adopter; 0 = non-adopter). For these response variables, a binary logistic regression model was applied by considering two modalities for each practice: adoption and non-adoption. Other intensive agricultural practices, such as cropping systems, variety use, and labor use, were treated and analyzed as multinomial response variables. In this context, a multinomial logistic regression model was employed following the recommendations of Shah et al. [44] and Ndeko et al. [37]. For the response variable “variety use,” the model compared the use of improved varieties alone and the combined use of improved and local varieties against the reference category of the use of local varieties alone. Similarly, for the response variable “labor use,” the modalities considered were the combined use of family and hired labor and the exclusive use of hired labor alone, using the exclusive use of family labor alone as the reference category.

The explanatory variables, summarized in Table 1, include structural characteristics of the farms (cultivated area, access to inputs and equipment), social and institutional

Table 1 Socioeconomic characteristics and land use of the farming households

Variables	Code	Unit	Description	M ± SD or %
Household size	HS	Number	Number of individuals in the household	8.98 ± 3
Age of household head	Age	Years	Age of the household head	42 ± 7.56
Gender (male)	Gender	Dummy	1 if household head is male, 0 if female	37
Education level	EL	Years	Number of years of formal schooling	3 (0–7)
Labor type	LT	Dummy	1: Family labor only; 2: Family and hired labor; 3: Hired labor only	29 / 58 / 13
Farming experience*	FE	Years	Number of years of experience in maize farming	19.57 ± 12.89
Non-agricultural income source (1)*	NAI	Dummy	1 if the farmer engages in non-agricultural activities, 0 otherwise	37
Access to credit (1)*	AC	Dummy	1 if the farmer has access to agricultural credit, 0 otherwise	31
Income from maize	IM	Dummy	< 25%, 25–49%, 50–75%, > 75%	4.2 / 23 / 32 / 41
<i>Land use and exploitation</i>				
Land area allocated to maize*	LAM	Are	Area dedicated to maize cultivation	4 (2, 10)
Total farmland area*	TFA	Are	Total land area owned by the farmer	8 (4, 15)
Land ownership by household head (1)*	LOH	Dummy	1 if the farmer owns the land, 0 otherwise	86
<i>Agricultural innovations</i>				
Maize variety type	MVT	Dummy	1: Local varieties; 2: Improved varieties; 3: Both local and improved varieties	23 / 60 / 16
Use of chemical fertilizers (1)*	UCF	Dummy	1 if the farmer applies chemical fertilizers, 0 otherwise	8.5
Use of organic inputs (1)*	UOI	Dummy	1 if the farmer applies organic fertilizers, 0 otherwise	78
Use of pesticides (1)*	UP	Dummy	1 if the farmer uses chemical pesticides, 0 otherwise	
Crop diversity*	CD	Number	Number of crop species grown in addition to maize	1.63 ± 1.21
Cropping system (monocropping)*	CS	Dummy	1 if maize is grown as a sole crop, 0 if intercropped	25
Number of associated crops*	NAC	Number	Number of crops intercropped with maize	3.52 ± 1.29
Contact with extension services (1)*	CES	Dummy	1 if at least one extension visit/year, 0 otherwise	17
Distance between home and field (far)*	DHF	Dummy	1 if the field is considered far, 0 otherwise (farmer's perception)	61
<i>Production constraints</i>				
Low soil fertility	LSF	Score	Soil fertility index (1 = low, 2 = moderate, 3 = high)	1.84 ± 0.69
Labor shortage	LS	Score	Labor availability index (1 = insufficient, 2 = moderate, 3 = sufficient)	1.62 ± 0.60
Lack of arable land	LAL	Score	Land availability index (1 = low, 2 = moderate, 3 = high)	1.58 ± 0.59
Unavailability of quality seeds	UQS	Score	Seed availability index (1 = available, 2 = moderately available, 3 = difficult to obtain)	1.65 ± 0.60
Low availability and high cost of fertilizers	LAHC	Score	Input availability index (1 = easily available, 2 = limited access, 3 = difficult to obtain)	1.72 ± 0.72
Market constraints	MC	Score	Index ranging from 1 to 3	1.82 ± 0.53
Post-harvest losses	PHL	Score	Index ranging from 1 to 3	2.06 ± 0.48
Institutional constraints	IC	Score	Index ranging from 1 to 3	2.30 ± 0.68
Weeding difficulties	WD	Score	Index ranging from 1 to 3	1.82 ± 0.74

attributes (membership in farmers' organizations, training, and contact with extension services), as well as contextual factors such as geographic location, pedoclimatic conditions, labor availability, and market accessibility. The general form of the model is expressed as follows:

$$\log \left(\frac{P(Y = j)}{P(Y = base)} \right) = \beta_{0j} + \beta_{1j}X_1 + \beta_{2j}X_2 + \cdots + \beta_{kj}X_k$$

Where Y represents the level of adoption of intensive practices, j denotes the adoption category (medium or high), X_k refers to the set of explanatory variables, and β_{kj} represents the estimated coefficients associated with each adoption category.

The model results allowed for the precise identification of producer profiles most likely to adopt agricultural intensification practices, in line with the approach described by Kim et al. [25]. They also enable the quantification of the relative impact of each explanatory factor on the probability of adopting a given practice. These outputs provide a basis for proposing targeted intervention strategies to strengthen adoption in groups where it remains low. Particular attention was given to the interaction effects between variables [53] to inform differentiated support policies tailored to each type of producer and their specific local context.

3.3 Data analysis

The dataset was first preprocessed by applying a logarithmic transformation to highly skewed quantitative variables, followed by the computation of descriptive statistics to characterize all measured parameters. A Principal Component Analysis (PCA) performed on 17 standardized variables was then used to reduce dimensionality and identify the major gradients of variation, after confirming the suitability of the data using the KMO index (>0.6) and Bartlett's test of sphericity ($p < 0.0001$). The retained components subsequently served as the basis for a Hierarchical Cluster Analysis using Ward's method, allowing the farms to be grouped into homogeneous typologies; differences among clusters were assessed using Kruskal-Wallis tests and Fisher's exact tests for categorical variables. The Kruskal-Wallis test was used because the data were not normally distributed. Normality of quantitative variables was assessed using the Shapiro-Wilk test, complemented by visual inspection of histograms and Q-Q plots. The determinants of the adoption of intensive agricultural practices were examined using multinomial and binary logistic regression models, as well as Firth's penalized logistic regression when complete data separation was detected, with multicollinearity verified through VIF values (<2.5). All statistical analyses were conducted in R version 4.5.1. The GPS coordinates of the surveyed farms were collected in the field using handheld Global Positioning System (GPS) devices and recorded in decimal degree format. The spatial data were then imported into ArcGIS 10.4 for mapping and spatial analysis in order to explore the distribution of the identified farmer typologies across the study.

4 Results

4.1 Typology and functional characterization of smallholder maize-producing farms

The scree plot (Fig. 3A, B) shows that the first two dimensions account for a substantial proportion of the total variance in the data, explaining 23.3% and 15.1%, respectively, cumulatively contributing 38.4%. This suggests that most of the structural information

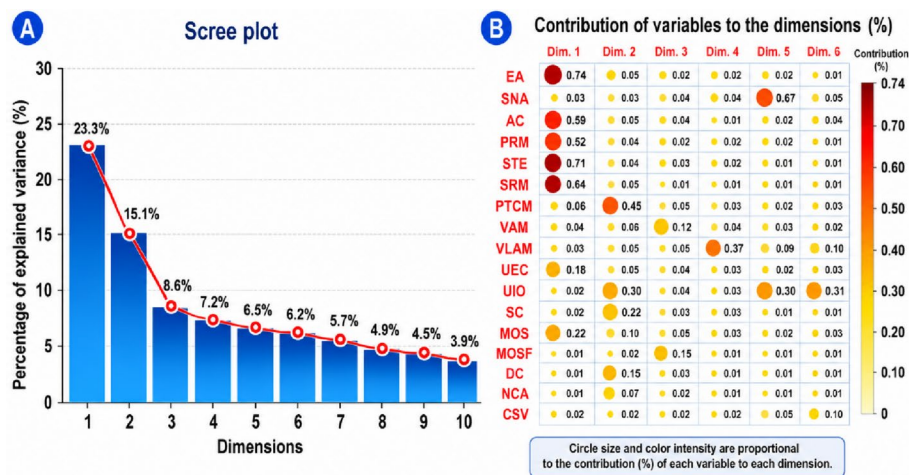


Fig. 3 Representation of the factorial axes derived from principal component analysis (PCA): **(A)** percentage of variance explained by each dimension and **(B)** correlations of variables with the first six principal components

is captured by these two principal components. The results indicate that the first dimension is strongly correlated with variables such as agricultural experience (EA), total farm size (STE), area allocated to maize (SRM), access to credit (AC), agricultural income (PRM), and the use of chemical fertilizers (UEC). This dimension reflects an economic intensification strategy, characterizing farms with greater resource endowment, more productivity-oriented, and driven by yield maximization. In contrast, the second dimension (15.1% of the variance) is associated with crop diversity (DC), the number of associated crops (NCA), the combination of local and improved varieties (VMLA), and contact with extension services (CSV). It represents an ecological intensification strategy, based on crop diversification, sustainability, and the resilience of production systems. The PCA thus highlights two major profiles of farming systems. The first corresponds to economically oriented intensive farms that mobilize greater capital and technical resources. The second includes ecologically oriented diversified farms, which prioritize sustainability, diversity, and adaptation to local constraints.

Following the Principal Component Analysis, Hierarchical Cluster Analysis (HCA) was performed on the factorial coordinates of the farms in order to group them (Fig. 4A, B). The dendrogram, constructed on the basis of similarity among farms in terms of cropping practices, land area, and input use, identified four main classes of farms. These classes correspond to contrasting profiles based on their degree of intensification and structural conditions.

4.1.1 Characterization of the typology

The results reveal marked heterogeneity among the four types of producers, with statistically significant differences ($p < 0.05$) for nearly all variables (Table 2). Producers in Type 1 (43.5%) exhibit the lowest levels of agricultural experience and cultivated land area, yet they practice almost exclusively crop association (99.2%). They make very limited use of chemical fertilizers (4.1%) while widely adopting organic inputs (94.3%). Type 2 (12.7%), characterized by extensive experience (30.9 years) and the largest farm sizes, also shows high access to credit (83.3%) and substantial adoption of chemical fertilizers (52.8%), but very limited use of improved varieties alone. Type 3 (33.9%) is distinguished

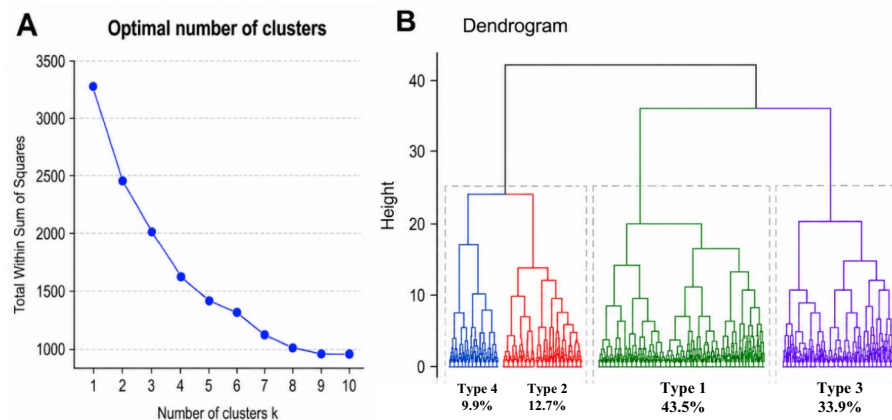


Fig. 4 Determination of the optimal number of classes (A) and (B) hierarchical clustering dendrogram of agricultural holdings

by lower crop diversity and a frequent use of combined local and improved varieties (59.4%), while showing the lowest adoption rate of organic inputs (44.8%). Type 4 (9.9%), composed of highly experienced producers (35.8 years) with large cultivated areas, is characterized by systematic use of organic inputs (100%), complete absence of chemical fertilizer use, and a strong dependence on maize-related income (46.4% earning more than 75% of their income from maize).

4.1.2 Functional characterization of maize-producing farms

The characterization of the functioning of the different typologies of maize farms is presented in Table 2. The results show that the differences observed in access to credit, land ownership, the types of varieties used, and fertilization practices reveal contrasting production systems, ranging from low-capital but diversified farmers (Type 1) to more intensive and financially integrated producers (Type 2), as well as intermediate mixed systems (Type 3) and mature producers oriented toward organic practices (Type 4). The socio-economic characteristics of maize producers show significant differences across the four identified types. Mean age ranges from 40 ± 7.67 years among Type 3 producers to 46.9 ± 5.26 years in Type 4 ($p = 0.0002$), suggesting a stronger presence of experienced households in the latter group. Household size also differs, with higher values observed in Types 2 (10.56 ± 4.98 persons) and 4 (10.25 ± 2.89), compared to the smaller household sizes of Types 1 and 3 ($p = 0.0009$).

Labor use reveals very pronounced contrasts ($p < 0.0001$): Type 2 relies exclusively on hired labor (100%), whereas Type 1 mainly mobilizes a family-hired labor combination (66.7%), and Type 4 also makes extensive use of this combination (92.9%). Finally, the distance between the field and the household strongly differentiates the groups ($p < 0.0001$). Types 2 and 3 have 75% of their plots located far from the homestead, in contrast to Type 1, whose fields are predominantly nearby (52.8%), while Type 4 shows a more balanced distribution (61% far and 39% near).

Constraints to maize production vary considerably across producer types. Low soil fertility is predominantly perceived as a moderate to severe constraint, particularly among Types 2 and 4. Labor shortages represent a major limitation for Types 3 and 4, where more than two-thirds of producers consider it severe. The shortage of cultivable land mainly affects Types 2 and 4, although the overall difference remains marginal. The

Table 2 Characterization of maize-producing farm typologies and their functional dynamics in relation to maize production constraints

Variables	Modalities	Type 1 (43.5%)	Type 2 (12.7%)	Type 3 (33.9%)	Type 4 (9.9%)	M ± SD or %	P-value
Variables used in the typology of maize producers							
Farming experience	Years	13.39 ± 8.01	30.92 ± 12.08	18.40 ± 12.20	35.79 ± 10.07	19.57 ± 12.89	< 0.0001
Total farm size (ha)	Ha	1.69 ± 0.68	3.53 ± 0.96	2.17 ± 0.58	3.79 ± 0.34	2.30 ± 1.01	< 0.0001
Area allocated to maize (ha)	Ha	1.19 ± 0.48	2.79 ± 0.92	1.76 ± 0.58	2.59 ± 0.40	1.72 ± 0.82	< 0.0001
Crop diversity	Number crops	2.41 ± 0.88	1.33 ± 1.24	0.60	2.10 ± 0.74	1.63 ± 1.21	< 0.0001
Number of associated crops	Number of crops	3.97 ± 0.91	3.91 ± 1.57	2.49 ± 1.01	4.58 ± 0.84	3.52 ± 1.29	< 0.0001
Cropping system	Intercropping (%)	99.2	69.4	39.6	100	75	< 0.001
	Monocropping (%)	0.8	30.6	60.4	0	25	
Other income sources	No (%)	98.4	100.0	100.0	100.0	99.3	0.7041
Access to credit	Yes (%)	1.6	0.0	0.0	0.0	0.7	
	No (%)	91.1	16.7	76.0	17.9	31	< 0.001
Income derived from maize	Yes (%)	8.9	83.3	24.0	82.1	69	
	< 25%	6.5	0.0	3.1	3.6	4.2	0.0076
	25–49%	25.2	5.6	30.2	14.3	23	
	50–75%	22.8	52.8	34.3	35.7	32	
	> 75%	45.5	41.7	32.3	46.4	41	
Land ownership	No	4.1	8.3	34.4	0.0	14	< 0.001
Type of maize varieties used	Yes	95.9	91.7	65.6	100.0	86	
	Local varieties	11.4	41.7	27.1	39.3	60	< 0.001
	Local + improved varieties	63.4	52.8	59.4	60.7	16	
	Improved varieties	25.2	5.6	13.5	0.0	23	
Use of chemical fertilizers	No	95.9	47.2	100.0	100.0	92	< 0.001
Use of organic inputs	Yes	4.1	52.8	0.0	0.0	8.5	
	No	5.7	5.6	55.2	0.0	22	< 0.001
Contact with extension services	Yes	94.3	94.4	44.8	100.0	78	
	No	83.7	75	79.2	100.0	17	0.016
	Yes	16.3	25	20.8	0.0	83	
	Other socio-economic characteristics						

Table 2 (continued)

Variables	Modalities	Type 1 (43.5%)	Type 2 (12.7%)	Type 3 (33.9%)	Type 4 (9.9%)	M ± SD or %	P-value
Age of household head	Years	42.1 ± 7.4	43 ± 7.56	40 ± 7.67	46.9 ± 5.26	42 ± 7.56	0.0002
Household size	Number of HH members	8.72 ± 1.83	10.56 ± 4.98	8.35 ± 3.01	10.25 ± 2.89	8.98 ± 3.00	0.0009
Type of labor used	Family labor only	32.5	0.0	41.7	7.1	29	< 0.0001
	Hired labor only	0.8	100.0	1.0	0.0	13	
	Both family and hired labor	66.7	0.0	57.3	92.9	58	
Distance between field and home	Far	47.2	75	75	60.7	61	< 0.0001
	Near	52.8	25	25	39.3	39	
Maize production constraints							
Low soil fertility	Low	20.3	2.8	22.9	0.0	17	0.02
	Medium	49.6	52.8	46.9	60.7	50	
	High	30.1	44.4	30.2	39.3	33	
Labor shortage	Low	8.1	8.3	5.2	0.0	6.4	< 0.0001
	Medium	67.5	52.8	31.2	25.0	49	
	High	24.4	28.9	63.5	75.0	45	
Lack of land for cultivation	Low	7.3	2.8	5.2	0.0	5.3	0.0647
	Medium	46.3	41.7	56.2	28.6	47	
	High	46.3	55.6	38.5	71.4	47	
Unavailability of quality seeds	Low	10.6	2.8	4.2	0.0	6.4	0.0002
	Medium	30.9	61.1	39.6	71.4	52	
	High	58.5	36.1	56.2	28.6	42	
Low availability and high cost of fertilizers	Low	17.1	0.0	24.0	3.3	16	< 0.0001
	Medium	55.3	27.8	30.2	25.0	40	
	High	27.6	72.2	45.8	71.4	44	
Marketing constraints	Low	4.1	8.3	9.4	3.6	6.4	< 0.0001
	Medium	8.9	50.0	61.5	51.1	69	
	High	87.0	41.7	29.2	39.3	25	
Post-harvest losses	Low	9.8	0.0	30.2	3.6	15	< 0.0001
	Medium	81.3	80.6	66.7	85.7	77	
	High	8.9	19.4	3.1	10.7	8.5	
Institutional constraints	Low	18.7	80.6	50.0	75.0	42	< 0.0001
	Medium	65.9	11.1	37.5	25.0	45	
	High	15.5	8.3	13.5	0.0	12	
Weeding difficulties	Low	13.8	0.0	40.6	3.6	20	< 0.0001
	Medium	74.0	13.9	21.9	0.0	41	
	High	12.2	86.1	37.5	96.4	39	

unavailability of quality seeds affects Types 1 and 3 more strongly, as they report higher levels of severity than the other groups. Fertilizers, due to their high cost and limited availability, constitute a critical constraint for Types 2 and 4. Marketing difficulties are especially prominent among Type 1 producers, who face significantly greater obstacles

than the other groups. Post-harvest losses remain moderate to high in Types 1 and 2, whereas Type 3 appears relatively less affected. Institutional constraints show strong contrasts across producer types: they are low for Types 2 and 4 but considerably more pronounced for Types 1 and 3. Finally, weeding difficulties are particularly severe among Types 2 and 4, revealing substantial limitations in access to labor or appropriate tools for field operations.

4.2 Spatial distribution of maize farm holdings in South Kivu

Figure 5 illustrates the spatial distribution and proportional representation of the four farm typologies identified across the three study territories (Kabare, Uvira, and Walungu) in South Kivu Province. The spatial analysis revealed a heterogeneous distribution of the typologies across the study area, with a predominance of Type 1 farms in almost all territories. In Kabare Territory, Type 1 represented 51.1% of the surveyed farms, followed by Type 2 (24.4%), Type 3 (16.7%), and Type 4 (7.8%). Similarly, in Walungu Territory, Type 1 was the dominant group, accounting for 65.0% of farms, whereas Type 4 represented 21.0%, while Types 2 and 3 contributed only 9.0% and 5.0%, respectively. The geographical map further confirmed that Type 1 farms were widely dispersed throughout the territories, indicating their strong ecological and socio-economic adaptability within the study region.

Conversely, Uvira Territory exhibited a markedly different typological structure characterized by the overwhelming dominance of Type 3 farms, which accounted for 81.7% of the surveyed households. The proportions of Type 1 and Type 2 were considerably lower, representing 12.9% and 5.4%, respectively, while Type 4 was absent in this territory. This distinct territorial configuration suggests the existence of specific agroecological, socio-economic, or market-related conditions shaping farming systems in Uvira. Overall, the observed territorial variability in farm typologies highlights the strong influence of local environmental conditions and production strategies on the organization of agricultural systems in South Kivu. These findings demonstrate that farming systems are not uniformly distributed across territories but are spatially structured according to

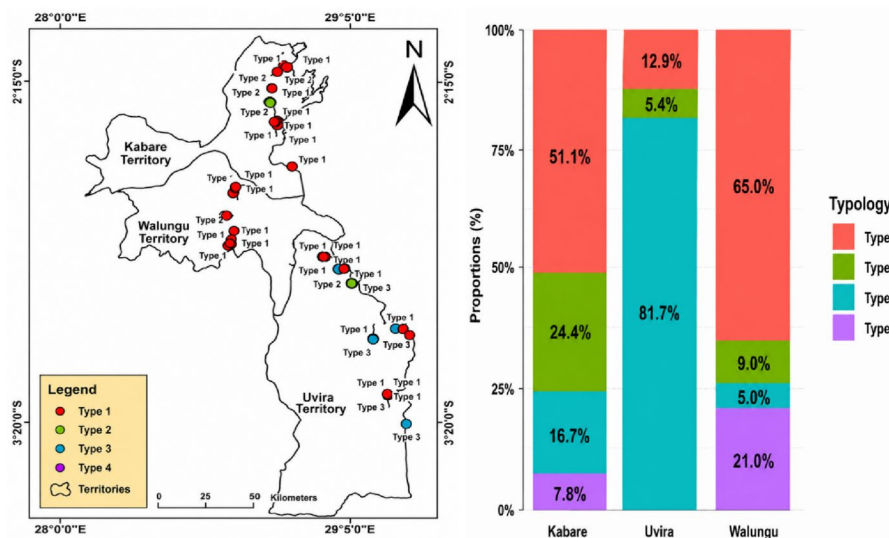


Fig. 5 Spatial distribution of maize-producing farm typologies across different geographic zones of South Kivu

local resource availability, production orientation, and farmers' adaptive responses to environmental and socio-economic constraints.

4.3 Identification of intensive agricultural practices used by farmers

Figure 6 highlights important territorial differences in the adoption of agricultural practices across Kabare, Uvira, and Walungu. Organic fertilizers recorded very high adoption rates in Kabare (about 99%) and Walungu (about 90%), while adoption was lower in Uvira (around 45%). In contrast, chemical fertilizers showed very high non-adoption rates in all territories, reaching nearly 88% in Kabare, 100% in Uvira, and about 92% in Walungu, whereas adoption levels remained below 15%. These findings suggest that farmers largely rely on locally available organic nutrient management practices rather than costly mineral fertilizers. Similarly, diversified cropping systems were widely adopted, particularly in Walungu (approximately 97%) and Kabare (about 88%), while adoption was moderate in Uvira (around 40%). Labor utilization was predominantly based on a combination of hired labor and family workforce, accounting for approximately 54% of farming households in Kabare, 60% in Uvira, and 59% in Walungu.

Regarding crop varieties, local varieties predominated in all territories, accounting for approximately 61% in Kabare, 52% in Uvira, and 66% in Walungu. Improved varieties alone were less represented, with proportions ranging from about 15% in Walungu to 28% in Uvira. However, the combined use of local and improved varieties was also observed, particularly in Uvira (19%) and Walungu (17%), indicating a gradual integration of improved germplasm into traditional seed systems. The predominance of organic fertilizer adoption, diversified cropping systems, and local varieties demonstrates farmers' preference for low-cost and environmentally sustainable agricultural practices.

4.4 Factors influencing the adoption of intensive agricultural practices in maize cultivation

Table 3 presents the results of a Firth penalized logistic regression aimed at identifying factors influencing the adoption of chemical fertilizers by maize producers. The

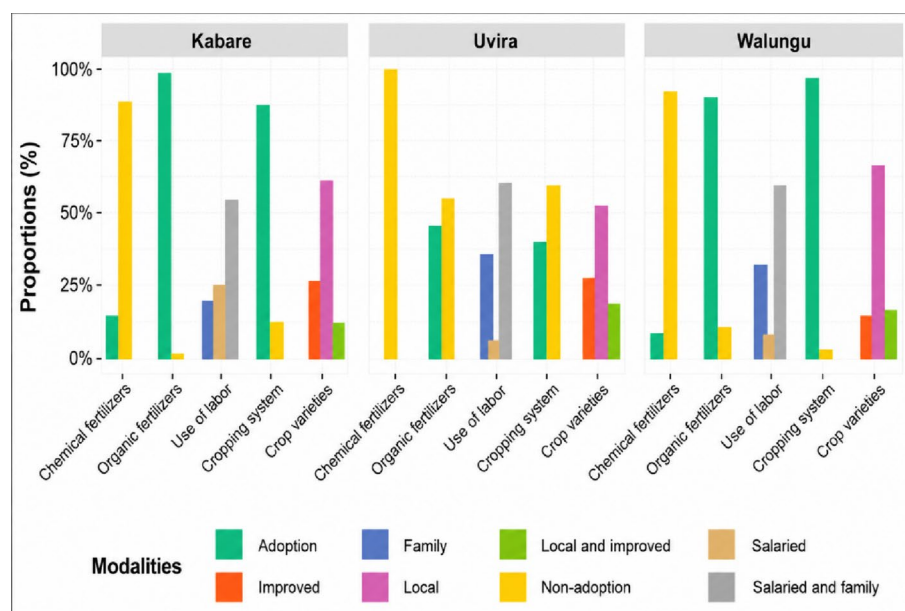


Fig. 6 Variation of intensive agricultural practices implemented across the three territories of South Kivu

Table 3 Factors influencing the adoption of agricultural practices in maize production

Variable	Chemical fertilizer		Organic fertilizer		Cropping system		Improved & local varieties		Improved varieties only		Family & hired labor		Hired labor only	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Constant	-5.93	<0.0001	-1.95	0.008	0.14	0.854	-0.21	0.827	-1.73	0.023	-1.02	0.16	-10.3	<0.0001
Age [26–35 years]	0.06	0.970	-0.66	0.298	-1.25	0.152	1.76	0.110	0.81	0.346	-0.82	0.19	5.58	<0.0001
Age [36–45 years]	0.63	0.643	0.11	0.829	1.54	0.012	0.83	0.336	-0.02	0.981	-0.06	0.89	-7.36	0.000
Age > 45 years	-0.81	0.415	-0.06	0.868	-0.26	0.531	-1.09	0.094	-0.35	0.412	-0.32	0.36	3.73	<0.0001
Farming experience	0.05	0.034	0.02	0.299	-0.02	0.295	-0.10	<0.0001	-0.02	0.225	0.05	0.007	0.13	<0.0001
Household size	0.06	0.342	0.18	0.004	0.14	0.021	-0.12	0.176	0.02	0.680	0.02	0.69	0.16	0.076
Membership of FBO	1.22	0.074	0.16	0.771	-0.34	0.461	0.77	0.247	0.22	0.629	0.36	0.49	1.51	0.046
Contact with extension services	-0.23	0.695	-0.76	0.151	-0.27	0.550	-0.32	0.631	0.22	0.634	0.31	0.58	-0.08	0.914
Land ownership	0.68	0.463	1.35	0.002	0.95	0.023	-0.22	0.710	-0.48	0.308	0.81	0.05	1.51	0.088
Distance field–home	0.25	0.649	0.48	0.214	0.87	0.014	0.08	0.857	0.41	0.252	-0.34	0.30	-0.24	0.687
Access to credit	0.54	0.360	0.45	0.392	-0.33	0.438	1.37	0.048	1.23	0.006	0.86	0.10	2.35	0.001
Moderate labor shortage	0.10	0.889	-1.23	0.015	-0.36	0.468	-0.28	0.649	0.74	0.200	-0.34	0.53	-1.23	0.112
Severe labor shortage	0.97	0.040	-0.76	0.038	-0.48	0.164	0.10	0.806	-0.01	0.975	-0.42	0.24	-0.53	0.332
Income from maize [25–49%]	0.71	0.507	0.06	0.912	-0.53	0.448	0.68	0.334	0.74	0.229	0.09	0.86	-0.09	0.926
Income from maize [50–75%]	-0.24	0.788	0.08	0.861	1.52	0.001	2.62	<0.0001	0.57	0.244	0.16	0.70	0.59	0.455
Income from maize > 75%	-0.33	0.621	-0.78	0.034	-0.12	0.735	-0.94	0.233	0.19	0.608	-0.18	0.58	-1.05	0.105
Moderate land shortage	-0.97	0.215	2.38	<0.0001	0.34	0.581	0.28	0.673	-0.02	0.972	0.22	0.68	0.02	0.982
Severe land shortage	0.32	0.547	0.10	0.762	-0.16	0.684	-0.36	0.425	-0.10	0.801	-0.24	0.50	-0.06	0.920

intercept is strongly negative (-5.93) and significant ($p < 0.0001$), indicating that in the absence of explanatory variables, the probability of adopting chemical fertilizers is very low. Among the variables, agricultural experience is significant (coefficient = 0.05; OR = 1.05; $p = 0.034$), suggesting that each additional year of experience slightly increases the likelihood of adoption. In contrast, a high labor shortage has a significant negative effect (coefficient = -0.97; OR = 0.38; $p = 0.040$), indicating that farms facing labor scarcity are less likely to use these inputs. Other factors, such as producer age, household size, membership in an association, contact with extension services, access to credit, and land ownership, do not have statistically significant effects ($p > 0.05$).

The analysis of the determinants of organic fertilizer adoption shows that the intercept is negative and significant (-1.95; OR = 0.14; $p = 0.008$), indicating that in the absence of explanatory factors, the probability of adopting organic fertilizers remains low. Among the significant variables, household size has a positive effect (coefficient = 0.18; OR = 1.20; $p = 0.004$), suggesting that larger households are more likely to use organic fertilizers. Land ownership also shows a strong positive effect (coefficient = 1.35; OR = 3.87; $p = 0.002$), indicating that land-owning producers are nearly four times more likely to adopt these inputs. Conversely, medium and high labor shortages significantly reduce adoption (coefficient = -1.23; OR = 0.29; $p = 0.015$ and coefficient = -0.76; OR = 0.47; $p = 0.038$), reflecting the constraint that labor availability poses for the management of organic fertilizers. High maize-derived income (> 75%) has a significant negative effect (coefficient = -0.78; OR = 0.46; $p = 0.034$), suggesting that producers highly dependent on maize are less inclined to use organic fertilizers. Interestingly, a medium shortage of land shows a very strong positive effect (coefficient = 2.38; OR = 10.79; $p < 0.0001$), indicating that, in this context, some producers with limited land opt to intensify production through organic fertilizers. Other variables, including age, agricultural experience, association membership, or access to credit, do not have statistically significant effects on adoption.

The results of the Firth penalized logistic regression analyzing the determinants of crop system choice among maize producers show that the intercept is not significant (coefficient = 0.14; OR = 1.15; $p = 0.854$), indicating that in the absence of explanatory variables, the probability of selecting a specific cropping system is undetermined. Among the significant variables, producers aged 36–45 years have a strong positive effect (coefficient = 1.54; OR = 4.67; $p = 0.012$), suggesting that this age group is nearly five times more likely to adopt a particular cropping system compared to other age groups. Household size also positively influences cropping system choice (coefficient = 0.14; OR = 1.15; $p = 0.021$), indicating that larger households have greater capacity to manage more intensive systems. Land ownership increases the likelihood of selecting certain systems (coefficient = 0.95; OR = 2.60; $p = 0.023$), as does the distance between the field and the household (coefficient = 0.87; OR = 2.38; $p = 0.014$), suggesting that producers with more distant plots favor particular management practices. Finally, intermediate maize-derived income (50–75%) is strongly associated with cropping system choice (coefficient = 1.52; OR = 4.59; $p = 0.001$), indicating that producers moderately dependent on maize are more likely to adopt a specific cropping system. Other variables, including agricultural experience, association membership, access to credit, or land and labor shortages, do not have statistically significant effects on cropping system choice.

For the adoption of local and improved varieties, a multinomial logistic regression was applied using the sole use of local varieties as the reference category. The results show that agricultural experience has a significant negative effect (coefficient = -0.10; OR = 0.90; $p < 0.0001$), suggesting that more experienced producers are less likely to combine local and improved seeds. Maize-derived income between 50 and 75% strongly increases the probability of adopting both types of varieties (OR = 13.67; $p < 0.0001$). Access to credit also promotes this adoption (OR = 3.93; $p = 0.048$), indicating that producers with financial resources are more likely to diversify their seed use. Other factors, such as age, household size, association membership, land ownership, or labor shortages, do not have a significant effect. For the adoption of improved varieties only, the negative and significant intercept (coefficient = -1.73; OR = 0.18; $p = 0.023$) indicates that, in the absence of explanatory variables, the probability of adopting improved varieties alone is low. Access to credit is the most influential factor for this group (OR = 3.41; $p = 0.006$), highlighting the importance of financial resources for acquiring improved seeds. Other variables, including agricultural experience, age, household size, maize-derived income, and land or labor shortages, do not show statistically significant effects on the exclusive adoption of improved varieties.

The model results indicate that the determinants of labor adoption vary considerably depending on whether a mixed labor system (family and hired labor) or exclusively hired labor is used. For the mixed system, only agricultural experience (OR = 1.05; $p = 0.007$) and land ownership (OR = 2.25; $p = 0.050$) significantly influence its adoption, suggesting that more experienced producers or landowners are more likely to simultaneously mobilize family and hired labor. In contrast, for the exclusive use of hired labor, several socio-economic factors have a pronounced effect: young producers (26–35 years) show an extremely high probability of employing hired labor (OR = 265.60; $p < 0.0001$), as do those older than 45 years (OR = 41.79; $p < 0.0001$). Agricultural experience also significantly reinforces this adoption (OR = 1.14; $p < 0.0001$). Moreover, association membership (OR = 4.53; $p = 0.046$) and access to credit (OR = 10.49; $p = 0.001$) play key roles, indicating that social networks and financial resources facilitate the ability to hire labor. Household size, labor shortages, field-to-home distance, and maize-derived income do not have statistically significant effects in either model. Overall, these results reveal that the adoption of hired labor relies primarily on economic resources and organizational dynamics, whereas the mixed labor system depends mainly on experience and land security.

5 Discussion

5.1 Typology and characterization of maize farming systems in South Kivu

The typological analysis derived from the hierarchical classification reveals substantial heterogeneity among maize farming systems in South Kivu, reflecting the coexistence of diverse production models. This diversity is primarily driven by differential access to productive resources, economic capital, and credit, as well as variation in farmers' experience levels and technical capacity. These findings are consistent with the observations of Tiftonell et al. [52] and Chikowo et al. [9], who argue that heterogeneity in African farming systems is shaped more by socio-economic and institutional conditions than by biophysical factors alone. The first cluster, characterized as low-intensity farms, groups the majority of producers and is marked by limited capital endowment, reliance

on family labor, and minimal use of chemical inputs. This profile corresponds to subsistence-oriented agriculture, similar to that described by Jayne et al. [23] and Ndeko et al. [36], where farmers have poor access to credit and depend heavily on the natural fertility of soils. The second cluster, composed of farms with larger landholdings and moderate adoption of inputs, reflects a transitional agriculture combining both organic and chemical inputs, with comparatively better access to financial services. This pattern aligns with the conclusions of Bekunda et al. [8] and Abera et al. [2], who highlight that access to credit and inputs is a key lever for sustainable intensification.

The third cluster, corresponding to diversified farms with partial adoption, illustrates a more ecologically oriented intensification pathway based on crop diversification and the pursuit of household food security. This profile resembles the intermediate forms of intensification identified by Teixeira et al. [50] and Ndeko et al. [36] in mixed smallholder systems across Africa. Finally, the fourth cluster, composed of highly intensive and specialized farms, reflects a commercial orientation focused on productivity through systematic use of fertilizers and hired labor. These findings are in agreement with those of Kuivanen et al. [27] and Hamazakaza et al. [22], who report the emergence of entrepreneurial farmers in high-potential zones. Overall, this typology reveals two distinct pathways of intensification: an economic pathway oriented toward profitability and specialization, and an ecological pathway emphasizing sustainability and diversification. These dynamics confirm the coexistence of contrasting agricultural models in South Kivu, as also demonstrated by Mwabila et al. [35] and Cirimwami et al. [12]. The key challenge remains the promotion of sustainable and inclusive intensification, supported by improved access to inputs, credit, and extension services, in line with recommendations from the FAO [18] and Bekunda et al. [8].

5.2 Spatial distribution of maize farming typologies in South Kivu

The analysis of the spatial distribution of maize farms in South Kivu reveals pronounced territorial disparities in the adoption of intensive agricultural practices. The territories of Kabare and Walungu are characterized by a high concentration of farms belonging to the moderately and highly intensive classes, indicating a strong dynamic of agricultural innovation. This clustering of intensive practices in central zones is largely explained by better access to markets, agricultural inputs, and extension services [21]. Similar patterns have been reported by Tittone et al. [52] and Chikowo et al. [9], who observed that proximity to economic hubs promotes investment and the modernization of production systems.

In contrast, the territory of Uvira is dominated by low-intensity farms, reflecting more traditional agricultural systems with limited institutional support. This pattern highlights persistent structural constraints, including inadequate access to credit, limited extension services, and shortages of skilled labor. These findings align with those of Jayne et al. [23] and Kuivanen et al. [27], who emphasize that peripheral regions often face disproportionate barriers to adopting agricultural innovations. Taken together, the results point to a decreasing gradient of intensification from Kabare towards Uvira, underscoring the dual nature of the provincial agricultural landscape. On one hand, economically and technologically driven intensification prevails in more connected zones; on the other, subsistence-oriented agriculture persists in more isolated areas. This trend corroborates the observations of Bekunda et al. [8] and Ndeko et al. [36], who highlight

the central role of technical support, infrastructure, and input availability in enabling the sustainable diffusion of intensive practices.

5.3 Intensive agricultural practices implemented by maize producers

The analysis of intensive agricultural practices in South Kivu reveals significant territorial disparities in the adoption of innovations. The limited use of chemical fertilizers across all territories, particularly in Uvira, highlights constraints related to input accessibility and the persistence of traditional farming practices, a situation consistent with the findings of Doss [14] and Tiftonell et al. [52]. In contrast, the widespread use of organic fertilizers in Kabare and Walungu reflects a form of intensification adapted to locally available resources, aligning with observations by Bekunda et al. [8] and Teixeira et al. [50], who emphasize the central role of organic inputs in the sustainability of farming systems. Labor organization, predominantly based on a mixed system combining family labor and hired workers, indicates that farmers seek to balance flexibility with sufficient production capacity. This structure mirrors the patterns described by Jayne et al. [23] and Kuivanen et al. [27], who note that such mixed labor arrangements are typical of farms undergoing gradual intensification while still relying on household resources.

Crop diversification, widely practiced in Kabare and Walungu but less common in Uvira, reflects an ecological intensification strategy that enhances food security and generates additional income, in agreement with findings by Ndeko et al. [36] and Mwabila et al. [35]. The adoption of improved maize varieties remains partial, with most farmers continuing to rely on local seeds. This trend illustrates a gradual uptake of innovations and echoes the observations of Cirimwami et al. [12] and Hamazakaza et al. [22], who highlight persistent barriers to varietal dissemination in African smallholder systems. Overall, farms in Kabare and Walungu combine the use of organic inputs, diversified cropping systems, and mixed labor arrangements, illustrating a moderate and progressive form of intensification. Conversely, Uvira remains characterized by traditional practices. These results reveal the coexistence of contrasting agricultural trajectories: ecological and partially commercial intensification in central territories, and subsistence-oriented agriculture in more peripheral areas. This pattern underscores the need for differentiated support strategies to foster sustainable adoption of intensive practices [8, 18].

The use of chemical fertilizers remains very low across all three territories, due to their high cost, limited accessibility, and farmers' preference for traditional practices. Producers with better access to credit or higher income from maize production exhibit a greater likelihood of applying chemical fertilizers, confirming the critical role of financial resources in agricultural intensification. These observations are consistent with the conclusions of Bekunda et al. [8] and Tiftonell et al. [52], who emphasize that economic capacity strongly conditions the adoption of modern inputs, and that better-capitalized farms tend to use more chemical fertilizers to maximize yields.

5.4 Factors influencing the adoption of intensive agricultural practices

In contrast, organic fertilizers are widely adopted, particularly in Kabare and Walungu, reflecting a form of intensification that is more ecological than economic. The availability of local resources and access to organic materials facilitate this practice, which helps maintain soil fertility while securing food production. This pattern is consistent with the

findings of Tittone et al. [52] and Barrett et al. [7], who reported that in low-capital areas, farmers prioritize inputs that are readily available and low-cost, thereby enhancing the sustainability of agricultural systems while minimizing economic risks.

Regarding the adoption of intercropping systems, farmer age appears as a key determinant. Producers aged 36–45 are significantly more likely to implement crop associations, suggesting that life experience and managerial maturity promote diversification. This observation aligns with Tittone et al. [52] and Barrett et al. [7], who highlighted that age and experience influence the capacity to manage complex farming systems and to spread production-related risks. Moreover, land ownership and proximity of plots further increase the likelihood of adopting intercropping, emphasizing the importance of land tenure security and accessibility for implementing labor-intensive and management-demanding practices. Agricultural income, particularly when maize contributes substantially to overall earnings, also emerges as a key factor, reflecting the economic incentive to diversify crops for both income stabilization and yield optimization [35].

For the adoption of improved or mixed maize varieties, agricultural experience negatively influences the combined use of local and improved seeds. More experienced farmers tend to specialize in a single seed type, likely due to practical knowledge and risk aversion. In contrast, access to credit acts as a strong enabler, facilitating the purchase of improved seeds while allowing retention of local varieties to secure production. These results corroborate the findings of Ndeko et al. [37, 39], which showed that varietal preferences are strongly shaped by financial capacity and the need to mitigate agricultural risks, and that partial adoption of improved varieties is central to maize improvement in resource-limited areas. Higher maize-derived income further reinforces this trend, indicating that profitability encourages the adoption of more intensive and diversified practices, as also noted by Bekunda et al. [8] and Teixeira et al. [50]. Regarding labor organization, results show that mixed family and hired labor is the predominant model, whereas exclusive reliance on hired labor is significantly influenced by age, experience, access to credit, and membership in farmer associations. These patterns reflect a strategic adaptation by farms to manage larger plots or implement intensive practices. These findings align with those of Kuivanen et al. [27] and Hamazakaza et al. [22], who emphasized that financial and institutional resources facilitate the employment of hired labor and support agricultural intensification.

The territorial disparities observed, particularly the very low use of chemical fertilizers in Uvira, likely reflect local contextual conditions such as differences in market accessibility, infrastructure, and input supply systems, in addition to farmers' production strategies and economic capacities. Recent studies in Sub-Saharan Africa have shown that access to agricultural inputs is often shaped by territorial connectivity, market organization, and the effectiveness of extension services [1, 17]. However, these contextual factors also constitute an integral part of the farming environment and therefore contribute meaningfully to understanding local adoption patterns. This study is based on cross-sectional survey data collected during a specific agricultural period, providing a representation of farming practices and adoption dynamics at the time of the survey. Although adoption levels may evolve according to seasonal conditions, climatic variability, input prices, or household economic situations, cross-sectional approaches remain widely used and appropriate for identifying major determinants and typologies of farming systems. Recent literature nevertheless highlights that adoption processes

among smallholder farmers are dynamic and may evolve over time depending on changing socio-economic and environmental conditions [15, 56, 57]. Future longitudinal and multi-season studies could therefore complement the present findings by providing deeper insights into the long-term evolution and sustainability of agricultural intensification pathways in South Kivu.

6 Conclusion

This study provides a comprehensive characterization of maize farming systems and the adoption of intensive agricultural practices in South Kivu, Democratic Republic of Congo. Through a combination of multivariate statistical analyses and geospatial mapping, we identified four distinct farm typologies reflecting heterogeneous levels of intensification, resource access, and technical capacity among producers. Our results reveal a clear spatial gradient of intensification, with Kabare and Walungu exhibiting moderate to high adoption of intensive practices, while Uvira remains dominated by low-intensity, subsistence-oriented farms. The adoption of intensive practices is strongly influenced by both socio-economic and structural factors, including farmer age, experience, access to credit, land tenure, proximity of plots, and maize-derived income as shown in the logistic regression model. Organic fertilizers and intercropping systems are widely adopted in central territories, reflecting ecological intensification adapted to local resources, whereas chemical fertilizers and improved seed varieties remain limited and are primarily utilized by better-capitalized producers. Labor organization, particularly the combination of family and hired labor, also plays a critical role in supporting more intensive cultivation.

These findings highlight the coexistence of contrasting agricultural trajectories in South Kivu: an economically oriented intensification in well-connected zones and an ecologically oriented, diversified, but low-input system in peripheral areas. Promoting sustainable intensification, therefore requires context-specific interventions, including improved access to inputs, credit, technical advisory services, and support for diversified cropping systems. Such targeted strategies are essential to enhance productivity, secure food systems, and foster inclusive agricultural development in the region.

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Author contributions

A.B.N. conceptualized the study and designed the methodology. A.B.N., G.B.C., E.M.C., and J.R. collected the data. S.N.S. and A.B.N. performed the statistical analyses. A.B.N., S.N.S. and G.B.C. wrote the main manuscript text. E.M.C. and J.R. prepared Figures and Tables. All authors reviewed and approved the final manuscript.

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Data availability

All data supporting the findings of this study are fully available within the manuscript and its Supplementary Information files, and can be obtained upon request from the corresponding author.

Declarations

Ethics approval and consent to participate

This study was reviewed and approved by the «Centre Interdisciplinaire pour la Recherche en Éthique» of Université Evangélique en Afrique (UEA), which granted clearance to collect data from small-scale maize farmers in the study area in accordance with institutional ethical guidelines. Informed consent was obtained from all participants prior to the

commencement of each interview. Informed consent was obtained from all individual participants included in the study. Participation was voluntary, and respondents were informed about the objectives of the research, the confidentiality of the information collected, and their right to withdraw at any time without any consequences.

Consent for publication

All authors have read and approved the final version of the manuscript and consent to its publication in *Discover Sustainability*.

Competing interests

The authors declare no competing interests.

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