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Assessing Sustainable Intensification Options for Maize Across Diverse Farm Types in Central Malawi

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Abstract

Smallholder farming systems in Sub-Saharan Africa are heterogeneous in resource endowment and livelihood objectives, posing challenges for effective agricultural interventions. This study characterises farm system diversity in Mtunthama Extension Planning Area, Kasungu District, Malawi, and evaluates the suitability of sustainable intensification innovations across farm types. Data were collected through focus group discussions and household surveys involving 43 farming households. Maize was the focus crop because it is the staple food crop of the whole of Malawi and the crop with which legumes are rotated or intercropped in the sustainable intensification options evaluated. Principal Component Analysis was used to construct a farm typology, while innovation suitability was assessed using a multi-criteria decision analysis framework. Four distinct farm types were identified: High-Resource-Endowed farms (HRE), Moderately resource-endowed farms with Diversified Cropping systems (MDV), Moderately resource-endowed farms with Mixed crop-livestock orientation (MCL), and Resource-Constrained Maize-dominated farms (RCM). The multi-criteria assessment revealed substantial variation in suitability across types. Conservation agriculture recorded the highest overall score (0.68), followed by intercropping (0.54), while strip cropping showed the lowest (0.25). MDV achieved the highest overall innovation score (0.66), whereas MCL and RCM showed limited uptake. These findings demonstrate that sustainable intensification effectiveness is shaped by resource endowment and trade-offs between productivity, income, and sustainability. The decoupling of maize yield and household income suggests intensification pathways are context-specific. The framework provides a useful approach for identifying suitable practice combinations for each farm type and for designing targeted interventions.

Keywords: context-specific interventions; farm diversity; Malawi; climate resilience; typology

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1. Introduction

The global population is projected to reach approximately 9.7 billion by 2050, creating an urgent challenge for food security [1,2]. To meet the growing demands of this expanding population, agricultural production must increase at a rate that keeps pace with population growth. However, agricultural productivity is constrained by several global factors, including land scarcity due to population pressures and the adverse effects of climate change [1,2]. These challenges are particularly pronounced in Sub-Saharan Africa (SSA), where rapid population growth coincides with a heavy reliance on subsistence farming [3]. In SSA, the majority of farmers are smallholder farmers who primarily rely on subsistence agriculture for food and income [4,5]. However, these farmers face numerous challenges in producing adequate cereal and legume crops to meet their families' nutritional needs [5]. These challenges are exacerbated by limited access to resources [2,4], raising serious concerns about food security in Eastern and Southern Africa, where agriculture is predominantly rain-fed [6,7]. In response to these challenges, global policy initiatives have emphasised the need for sustainable agricultural development. In 2015, United Nations member states jointly pledged their support for 17 Sustainable Development Goals (SDGs), with SDG2 aiming to "end hunger, achieve food security and improved nutrition, and promote sustainable agriculture" by 2030 [3]. However, achieving SDG2 in SSA remains a significant challenge, as rapid population growth is projected to triple the demand for major cereals and double the demand for animal-sourced food by 2050 [1,2]. Additionally, climate change is expected to alter rainfall and temperature patterns, potentially creating climate conditions with no present-day analogues. Given these challenges, farmers must adopt adaptive farming systems that align with their environmental conditions while addressing the ongoing need for soil fertility management to sustain agricultural productivity.

While many challenges faced by smallholder farmers are common across regions, the interaction of biophysical and socio-economic factors results in farm diversity within and across landscapes. In most regions of SSA, soil types and fertility management practices have led to variations in soil health across farms [6,8]. Additionally, differences in resource endowment, land ownership, production orientation, and farm objectives further contribute to complex and dynamic farm typologies [9–13]. Recent advances in farm typology frameworks integrate ex-ante assessments and trade-off analyses to evaluate intervention impacts across heterogeneous systems [10,14]. The failure of agricultural technologies to account for this complexity has historically limited their adoption [15,16]; participatory and data-driven approaches now enable tailored interventions [4,17]. Understanding farm diversity through these lenses is critical to move beyond one-size-fits-all recommendations [4,10]. This approach improves the relevance, applicability, and adoption of agricultural innovations.

The concept of farm typologies helps identify farm groups based on similar attributes, including social, structural, and operational characteristics [10,13]. Participatory approaches have been used to categorise farms accordingly [10,18]. While community-based classifications offer advantages in farmer engagement, they may overlook individual farm-level variations. Since decision-making and production orientation are largely household-driven, farm classifications should reflect household characteristics rather than broad community traits. Increasingly, multivariate statistical techniques such as Principal Component Analysis (PCA), Multiple Correspondence Analysis (MCA), and Cluster Analysis have been used to identify farm typologies across diverse farming systems [9–11,13]. Agricultural production and productivity are central to achieving livelihood sustainability and food security, particularly in smallholder systems [10,19]. One promising approach to addressing the challenges faced by smallholder farmers is through farm clustering or typology identification, which groups farms with similar structural and functional characteristics. This approach enables the development of tailored farm designs and interventions that are more closely aligned

with the specific needs, resources, and goals of different farm types [10,13,19]. Beyond its role in improving farm-level decision-making, farm typology analysis supports broader development goals by facilitating the scaling of innovations, targeting of extension services, and formulation of policies that reflect on-the-ground realities [9,11].

In Malawi, as in much of Sub-Saharan Africa, smallholder farmers form the backbone of agricultural production. Legume integration is a cornerstone of sustainable intensification strategies due to its multifunctional roles: it can enhance soil fertility through biological nitrogen fixation, provide protein-rich food for improved nutrition, and offer marketable products for income diversification. Crucially, legumes present a diverse array of integration options, such as rotation, intercropping, and strip cropping, that can, in principle, be tailored to fit varying resource endowments and labour availability [20–23]. Yet, the persistent mismatch between uniform technology recommendations and diverse farmer realities means this potential remains underutilised.

Our study addresses this mismatch by applying a farm typology approach to better understand and classify the diversity of smallholder farming systems in Mtunthama Extension Planning Area (EPA), a representative smallholder farming region in central Malawi. By integrating multivariate statistical methods with participatory insights, the study identifies distinct farm types and their associated constraints. These types serve as a basis for designing more context-appropriate legume-based interventions, such as improved varieties, rotations, and resource-conserving practices, tailored to the specific capacities and challenges of each farm type. Ultimately, this research aims to contribute to more effective, equitable, and scalable agricultural innovations that enhance food security, soil fertility, and resilience in Malawi's smallholder sector.

The objective of this study was to characterise the diversity of farming systems in Mtunthama Extension Planning Area (EPA) in Kasungu District, central Malawi, with a particular focus on resource endowment and legume cultivation practices, and to generate actionable insights that could inform the design and targeting of sustainable intensification (SI) interventions at the farm level. Data from farm interviews and focus group discussions were analysed to identify constraints and opportunities across different farm categories, thus providing a nuanced understanding of the farming landscape.

2. Materials and Methods

2.1. Site Description

The climate in Kasungu district (Figure 1) is characterised by distinct seasonal variations. A cool and dry winter season occurs from May to August, with mean daily temperatures ranging from 17 to 27 °C. This is followed by a hot and dry season from September to October, with average daily temperatures between 25 and 37 °C. The warm, wet season extends from November to April, bringing the majority of annual rainfall (800–1000 mm) through convective storms, with mean daily temperatures of 20–30 °C. Peak rainfall typically occurs between December and March, coinciding with the cropping season. However, local variations in temperature and precipitation patterns are influenced by the area's complex topography.

The district's soils are predominantly medium-textured sandy loam, which are prone to erosion and fertility depletion. Patches of clay loam soils, which are more suitable for crop cultivation, are also found in the area. Poor agricultural practices, such as monocropping without soil conservation measures, contribute to soil degradation and fertility loss [6,8]. Maize is the staple food crop of the whole of Malawi, while tobacco is an important cash crop in the district. Legumes, which are grown by 65% of farmers, rank third in economic importance, with soybean and groundnuts occupying 15–20% of cultivated area, often intercropped with maize [20,23]. Both soybean and groundnut are grown for cash, while

groundnut is also utilised at home for dietary purposes. Secondary crops such as cassava and sweet potatoes are also cultivated as food and climate-resilient alternatives.

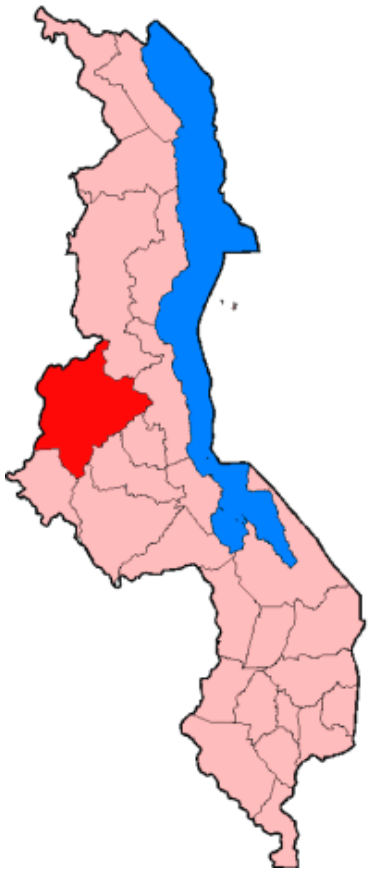


Figure 1. Map of Malawi showing district boundaries, highlighting the location of Kasungu District and the areas of interest, in red, with Lake Malawi visible on the north-eastern border in blue.

Farmers in Kasungu face significant challenges due to their reliance on rain-fed agriculture, small landholdings, limited access to agricultural inputs, and poor market linkages. As a result, many households struggle to meet their nutritional needs, a challenge documented in recent research on maize–legume systems in Malawi [21]. Farmers rear various livestock species, including cattle, sheep, goats, pigs, poultry, and rabbits. Livestock production remains limited, reducing the contribution of animal products to household food security and income [4]. While livestock populations have increased, the production and consumption of animal products remain low, exacerbating the food and nutrition issues highlighted previously [4].

The research was conducted across eight of twelve sections in Mtunthama EPA, providing a setting in which farm diversity can be examined under relatively lower land-fragmentation constraints. An Extension Planning Area (EPA), as defined by the Malawi Ministry of Agriculture in 2023, is a sub-district administrative unit that serves as the primary operational hub for delivering decentralised agricultural extension services, bridging the gap between district-level policy and field-level implementation for smallholder farmers.

2.2. Data Collection

2.2.1. Household Survey

A structured household survey was conducted through face-to-face interviews with 44 smallholder farmers in Mtunthama EPA. These farmers were purposively selected as they were participants in the SI-MFS mother–baby trials, serving as key contact points for

the co-design and testing of sustainable farming innovations. Data were collected using KoboToolbox, a digital survey tool that enabled efficient and accurate data capture in the field (www.kobotoolbox.org). The survey gathered detailed quantitative information on farm characteristics, resource endowments, management practices, and production constraints, providing a foundation for typology development and guiding targeted interventions.

2.2.2. On-Farm Trial Data

Maize grain yield (kg/ha) was recorded in the SI-MFS mother–baby on-farm trials hosted by the same farmers over two consecutive seasons (2023/24 and 2024/25). The trials followed a randomised complete block design with each farm as a block and six treatments per farm: conventional maize (ridged), sole maize with reduced tillage and mulch, maize–cowpea strip intercropping, maize–lablab strip intercropping, maize–cowpea rotation and maize–lablab rotation (the rotation treatments were managed as sole maize and sole legume in the first season, and rotation comparisons are limited to the second season). All plots measured 25 m × 15 m. Grain yield was determined from a net harvest area of 5 m length over the two central rows, shelled, weighed and corrected to 12.5% moisture content. For comparisons among farm types, farm-level yield was calculated as the mean of the two seasonal means across all maize treatments, excluding the first-season rotation plots, which served only as baseline because they were managed as sole maize; the farm mean therefore covers four treatments in the first season and six in the second and gives each season equal weight. The farm-type comparison of trial yield was unchanged when these baseline plots were included, when only the second season was used, and when only the four treatments common to both seasons were used (RCM significantly above MCL and MDV in every case). Trial records were matched to the surveyed households by farmer name; 34 of the 43 households in the typology could be matched (HRE 2, MDV 4, MCL 17, RCM 11) because trial-name information was missing for 9 farmers (HRE 1, MDV 2, MCL 3, RCM 3).

2.2.3. Focus Group Discussions

To understand smallholder farmers' perceptions, practices, challenges, and aspirations within Mtunthama EPA, a qualitative research approach was adopted using two Focus Group Discussions (FGDs). These discussions were part of the initial participatory activities under the Sustainable Intensification of Mixed Farming Systems (SI-MFS) initiative. The FGDs were conducted in August and September 2023 and took place at the Mtunthama EPA office, an accessible and centrally located venue for participants. Prior to the FGDs, introductory meetings were held with key stakeholders at the District Agriculture Office. These included officers from the crop, livestock, irrigation, food and nutrition, and planning departments. These preliminary engagements helped align the SI-MFS initiative with existing local development structures and provided valuable contextual insights into the district's agricultural systems. Participants for the FGDs were purposively selected to ensure diversity across gender and age groups and to reflect a range of farming experiences. Forty-five (45) farmers were involved in total, grouped into older men, younger men, and women. The participants were lead farmers or representative farmers from different villages within the EPA. Local extension officers and the research team facilitated participant mobilisation.

The discussions were conducted using a semi-structured interview guide designed to generate in-depth and context-specific insights into farmers' lived experiences and farming systems. The guide was developed collaboratively by SI-MFS researchers and was structured around three core questions:

- What are your main challenges related to productivity, environment, nutrition, human capital, and profitability?

- What are the most important value chains in your farming system, and what production practices support them?
- What changes or improvements do you aim to implement on your farm in the coming years?

Each focus group session lasted approximately 90 min and was facilitated by a trained moderator from the SI-MFS research team with support from local translators where necessary. Sessions were conducted in a neutral and comfortable setting to promote open and inclusive participation. Separate facilitators led each group to ensure tailored engagement and to reduce response bias.

2.3. Ethical Considerations

Ethical clearance for the study was obtained from the International Institute of Tropical Agriculture (IITA) Institutional Review Board (IRB/002/2023). Institutional permission to conduct the study was obtained from Chitedze Agricultural Research Station, Department of Agricultural Research Services (DARS), Ministry of Agriculture, Malawi (Ref. No. CZ/ADM/1/1, dated 22 July 2024). Participation was voluntary, and informed consent was obtained from all participating farmers. Confidentiality and privacy of participants were maintained throughout the study in accordance with the ethical requirements governing the research.

2.4. Data Analysis

All statistical analyses were conducted in R version 4.5.2 (R Foundation for Statistical Computing, Vienna, Austria), using the packages ade4 (v. 1.7.24) and FactoMineR (v. 2.16) (PCA), cluster (v. 2.1.8.2) and factoextra (v. 2.2.0) (cluster analysis), agricolae (v. 1.3.7) (analysis of variance and Tukey post hoc comparisons), rstatix (v. 1.1.0) (Welch ANOVA, Games–Howell, Kruskal–Wallis and Dunn tests) and car (v. 3.1.5) (Levene's test).

2.4.1. Farm Typology

Of the 44 surveyed households, one (farm 17) was excluded from the typology analysis because of an extreme livestock holding (about 23 TLU, compared with a maximum of 4.0 TLU among the remaining households) that would have dominated the multivariate solution, resulting in a final analytical sample of 43 households. The variables used for typology construction were selected based on literature [10,13], insights from the FGDs, and expert judgment. These variables captured differences in farming resources (land, labour), income streams (including off-farm income), integration of legumes (acreage, years of experience in growing legumes), tropical livestock units (TLUs), total labour inputs, cost of hiring labour, proportion of labour used for land preparation and weeding, crop and livestock enterprises, and the farmer's evaluation of legumes. From this candidate set, nine variables were retained as active variables in the final typology analysis; they are listed below.

Farm typologies were derived using a two-step cluster analysis applied to the principal components of nine continuous household variables. The active variables were: age of the household head (years), total household income (Malawi Kwacha), share of household income from farming (proportion), livestock holdings (tropical livestock units, TLUs), total landholding (acres), average maize production (kg per farm; the farmer-reported total maize harvest, not scaled by area), share of cultivated area under legumes (proportion), number of intensification options adopted, and number of sustainable practices adopted. All variables were treated as continuous, so no category coding was required. In summary, households were grouped according to their resource endowment (land, livestock and

income), maize production, legume integration, and the number of intensification options and sustainable practices adopted, together with age and the share of income from farming.

The variables were centred and scaled to unit variance and a PCA of the 43 × 9 data matrix was performed. The first four principal components were retained (eigenvalues 3.11, 1.54, 1.21 and 1.00; together explaining 76.4% of the total variance), based on the Kaiser criterion (eigenvalue > 1) and inspection of the scree plot (Section 3.2.1). In the first step, agglomerative hierarchical clustering with Ward's minimum-variance method (ward.D2) was applied to the Euclidean distances among households in the space of the four retained components, and the fusion coefficients (dendrogram heights) and the within-cluster sum-of-squares curve were examined to suggest an initial number of groups. In the second step, k-means clustering with four centres (k = 4) and 25 random starts (nstart = 25) was applied to the matrix of pairwise Euclidean distances to finalise group membership and maximise within-cluster homogeneity. The final number of clusters was determined by evaluating these statistical metrics together with the qualitative insights from the FGDs, following established typology development frameworks [9,10,13]. The four resulting farm types are referred to throughout as High-Resource-Endowed (HRE), Moderately resource-endowed with Diversified cropping (MDV), Moderately resource-endowed with Mixed crop–livestock orientation (MCL) and Resource-Constrained Maize-dominated (RCM) farms (Section 3.2.2).

2.4.2. Comparison of Farm Types

Differences in farm characteristics among the resulting farm types were tested for each variable (results in Section 3.3). Residual normality (Shapiro–Wilk test) and homogeneity of variance (Levene's test) were checked first. One-way ANOVA with Tukey's honestly significant difference test was used where both assumptions held; Welch's ANOVA with Games–Howell comparisons was used where they did not; and the Kruskal–Wallis test with Holm-adjusted Dunn comparisons was used for the share of income from farming and the number of intensification options, whose residuals were not normal. Maize production per acre of maize (production divided by total land multiplied by the share of land under maize) was analysed with Welch's ANOVA. Because most of these characteristics (all except on-farm trial maize yield) were also used to form the clusters, or are derived from clustering variables, the associated *p*-values describe how well the groups are separated and do not constitute an independent test of differences between farm types; they are therefore interpreted descriptively. On-farm trial maize yield was not used in the clustering and therefore provides a more independent comparison, although only 34 of the 43 farms could be matched to trial records. Because HRE comprised only three farms (two with trial records), non-significant comparisons involving HRE are inconclusive.

Education level was compared across farm types with a permutation chi-square test, because group sizes were small. For a visual comparison of the farm types, key productivity and resource-use variables were standardised to a 0–1 scale and displayed in a radar plot. Associations between livestock holdings (TLU) and (i) farmer-reported maize production, (ii) production per acre of maize and (iii) on-farm trial maize yield were assessed with Pearson and Spearman correlation coefficients.

2.5. Multi-Criteria Analysis for Targeting Sustainable Intensification Options

A Multi-Criteria Decision Analysis (MCDA) was used to evaluate and rank Sustainable Intensification (SI) options for suitability across the identified farm typologies. The analysis served as a decision-support framework to use farm typologies to derive tailored recommendations for technology use. It assessed disaggregated SI components (e.g., legume rotations, micro-dosing) against five weighted criteria: productivity potential, feasibility of adop-

tion, economic viability, resource use efficiency, and scalability. This approach aligns with frameworks that emphasise context-specific evaluation of agricultural innovations [24–27].

2.5.1. SI Innovation Disaggregation

The sustainable intensification (SI) options evaluated in this study were identified from practices currently implemented by farmers in the study area, based on focus group discussions and household survey data. These practices were not assessed as fixed technological packages but were instead operationalised as distinct innovation categories reflecting key management strategies observed in the field. The innovations considered included conservation agriculture, intercropping, small livestock integration, legume–maize rotation (cover cropping), and strip cropping.

Rather than evaluating individual technical components (e.g., minimum tillage or residue retention) in isolation, each innovation was represented using indicators derived from farmer-reported adoption and related management variables. These indicators were subsequently standardised on a 0–1 scale to enable comparison across farm types. The scaled scores were then aggregated to generate farm-type-specific performance values for each innovation, as well as an overall innovation score. This approach allowed for a comparative assessment of the relative performance and adoption of different SI practices across farm typologies, while reflecting the integrated nature of how these innovations are implemented in practice. Similar approaches have been used in multi-criteria assessments of farming systems to capture variation in technology performance across heterogeneous smallholder contexts [12,24,27], while research on sustainable intensification stresses the need to assess trade-offs across productivity, feasibility, and environmental outcomes [28].

2.5.2. Criteria Definition and Justification of Evaluation Criteria

Five evaluation criteria were selected to reflect key dimensions of sustainable intensification in smallholder farming systems, while remaining consistent with the variables available in the dataset. These criteria captured both biophysical performance and socio-economic feasibility, and were operationalised using quantitative indicators derived from household and farm-level data. In addition to generating composite innovation scores, each criterion was also retained as a separate indicator to allow for disaggregated analysis across farm types:

- **Productivity potential** was assessed using observed crop yields, particularly maize and legume yields derived from farmer records and plot-level data. Legume yields refer to cowpea (Vigna unguiculata) and lablab (Lablab purpureus) grown with maize in the SI-MFS mother–baby trials during the 2023/24 and 2024/25 seasons (maize–cowpea and maize–lablab rotations and strips, compared with sole conservation agriculture maize and conventional maize). These indicators capture the capacity of each innovation to contribute to crop output under existing management conditions.
- **Feasibility of adoption** was approximated using household resource endowment indicators, including landholding size (acres), livestock ownership (TLU), and labour availability (proxied by household size and labour-to-land ratios). These variables were standardised to a 0–1 scale and combined to reflect the relative capacity of households to implement different innovations.
- **Economic viability** was represented using farm income indicators, particularly income per hectare, as a proxy for the economic performance of farming activities.
- **Resource use efficiency** was assessed using indicators related to management practices, including the adoption of sustainable practices and integration of crop–livestock systems. Variables such as the count of sustainable practices and livestock density (TLU per acre) were used as proxies for the efficient use and recycling of farm resources.

- **Scalability and replicability** were inferred from the observed prevalence and distribution of innovations across farm types. Innovations that were widely adopted across multiple farm types were considered more scalable, while those concentrated within specific groups were interpreted as more context-dependent.

These criteria were selected not only for their relevance to smallholder contexts but also to comprehensively address the five dimensions of sustainable intensification assessed here: productivity potential, feasibility of adoption, economic viability, resource use efficiency and scalability [4,25,27].

2.5.3. Scoring and Weighting Procedure

Each farm type's performance under each SI innovation component was scored on a standardised 0–1 scale using min–max normalisation. Scores based on quantitative indicators (e.g., yield, income, land size, livestock units) were computed directly from household survey data and aggregated to farm type means. Specifically, the score of a farm type for an innovation is its mean value on the adoption-related indicator for that innovation, rescaled as $(x - \text{minimum})/(\text{maximum} - \text{minimum})$ across the four farm types. A score of 0 or 1 therefore denotes the lowest or highest value among the four farm types and not the absence or full level of adoption; for example, the intercropping score reflects the proportion of households in each farm type that practise intercropping.

For criteria where direct quantitative measurement was not feasible (e.g., residue utilisation and scalability), scores were derived through expert-informed assessment, based on consultations with extension officers and field observations collected during the study. In these cases, scoring reflected the relative suitability of each innovation for different farm types given their resource endowment profiles. For example, farm types with higher land, labour, and livestock resources were assigned higher feasibility scores for labour- and capital-intensive practices. The individual criterion-by-innovation scores and the notes from these expert-informed assessments were not retained, so they cannot be reproduced or reported.

To ensure consistency, all scoring procedures were guided by predefined criteria and cross-checked across the research team.

To avoid bias in aggregation, the five innovations were assigned equal weights (0.20 each) in the base model, so that the overall score of a farm type is the unweighted mean of its five innovation scores, following recent sustainable-intensification assessment guidance [24,26]. Sensitivity analyses were conducted using alternative weighting schemes to test the robustness of the results. Because farm-type-by-criterion score data were not retained for a criterion-level re-weighting, this sensitivity check was implemented by re-weighting the five sustainable intensification innovations reported in Section 3.5 rather than the five underlying scoring criteria; the weighting schemes and results are presented in Section 3.5 and, in full (weights, input scores, composite scores and ranks), in Supplementary Tables S1–S3. In the base model, each innovation had a weight of 0.20; in the economic-weighted scheme, the weight of small livestock integration was raised to 0.40; and in the resource-use-weighted scheme, the weight of legume–maize rotation was raised to 0.40 (0.15 for each of the other four innovations in both schemes). The sensitivity analysis therefore tests the stability of the farm-type scores to the weights given to individual innovations; it does not test, and no conclusion is drawn about, the stability of the five criterion weights. Because the criterion-level score matrix was not retained, the innovation scores in Section 3.5 are reported as aggregated, standardised (0–1) indices per farm type and should be read as relative, indicative suitability scores rather than as validated criterion-by-criterion assessments. The five criteria described in Section 2.5.2 were operationalised at the level of farm types, and criterion-level inputs for each innovation were not retained; the scores

therefore cannot be decomposed into criterion contributions or independently reproduced from the criterion scores.

The overall (composite) score of each farm type was calculated across the five innovations using a weighted additive model:

$$\text{Composite score} = \sum_{i=1}^{n} w_i \times s_{ij}$$

where:

- w_i is the weight of innovation i;
- s_{ij} is the scaled (0–1) score of innovation i for farm type j;
- n is the total number of innovations (5 in this case).

Multi-criteria analysis scores were used to rank SI innovations by their suitability for each farm typology. This process allowed for cross-type comparison and informed the most appropriate SI innovations per farm type. The MCDA thus complemented the farm typology and yield analysis by providing a structured, context-sensitive framework for matching SI interventions to the real-world constraints and opportunities faced by different smallholder farm households.

3. Results

3.1. Characteristics of the Surveyed Households

The 43 households included in the analysis were headed by farmers with a mean age of 44.7 years (range 32–66), and household size averaged 6.3 persons (Table 1). Primary (51.2%) and secondary education (44.2%) were the most common levels of household-head education; one head had tertiary education and one had never attended school. Farms were small, averaging 5.7 acres (median 5.0; range 1.0–25.0), of which an average of 43.2% was under maize and 41.4% under legumes. Livestock holdings were limited (mean 0.55 TLU; median 0.24); 33 households kept chickens, 23 kept goats and only two kept cattle. Mean household income was USD 722 (median USD 622), and farming contributed 85.6% of it on average. Access to credit was low (25.6% of households), whereas manure application to maize (72.1%), intercropping (74.4%) and integrated pest management (65.1%) were common; cover cropping (20.9%), irrigation (34.9%) and agroforestry trees (27.9%) were less common. The wide ranges in land, livestock and income indicate substantial heterogeneity among households, which motivates the farm typology presented in Section 3.2.

Table 1. Characteristics of the surveyed households ($n = 43$).

Variable	Mean ± SD or *n* (%)	Range
Age of household head (years)	44.7 ± 7.1	32–66
Household size (persons)	6.3 ± 2.2	3–13
Education of household head: primary, *n* (%)	22 (51.2)	–
Education: secondary, *n* (%)	19 (44.2)	–
Education: tertiary, *n* (%)	1 (2.3)	–
Education: never attended school, *n* (%)	1 (2.3)	–
Household income (USD)	722 ± 743	27–3804
Share of income from farming (%)	85.6 ± 17.6	10–100
Total landholding (acres)	5.7 ± 3.9	1.0–25.0
Livestock (TLU)	0.55 ± 0.74	0.00–4.00

Table 1. *Cont.*

Variable	Mean ± SD or *n* (%)	Range
Share of land under maize (%)	43.2 ± 14.4	12–100
Share of land under legumes (%)	41.4 ± 16.6	0–71
Intensification options (count)	1.33 ± 0.89	0–3
Sustainable practices (count)	2.53 ± 1.45	0–6
Access to credit, *n* (%)	11 (25.6)	–
Manure applied to maize, *n* (%)	31 (72.1)	–
Intercropping, *n* (%)	32 (74.4)	–
Integrated pest management, *n* (%)	28 (65.1)	–
Irrigation, *n* (%)	15 (34.9)	–
Cover cropping, *n* (%)	9 (20.9)	–
Agroforestry trees, *n* (%)	12 (27.9)	–

Note: Values are mean ± standard deviation unless n (%) is given. The sample excludes farm 17 (Section 2.4.1). Income was converted at 1 USD = 1840 Malawi Kwacha. TLU = tropical livestock unit. Credit refers to access to a loan during the 2022/23 season.

3.2. Farm Typology Construction

3.2.1. Principal Component Analysis

Principal Component Analysis (PCA) was conducted to reduce the dimensionality of the dataset and identify key underlying farm system characteristics. Four components with eigenvalues greater than one were retained based on the Kaiser criterion and scree plot inspection. Component 1 explained 34.6% of the variance, Component 2 explained 17.1%, Component 3 explained 13.5%, and Component 4 explained 11.2%, together explaining 76.4% of the total variance (Figure 2). The components can be interpreted from their loadings (Table 2; loadings with an absolute value of 0.5 or more are considered). Component 1 (34.6%) is a wealth and scale gradient: household income (0.83), total land (0.79), average maize production per farm (0.69; a farm total, so this loading partly reflects farm size) and livestock holdings (0.67) load positively, whereas the share of income from farming (−0.57) and the share of area under legumes (−0.55) load negatively, separating larger, wealthier farms from small farms that depend more on farming income and allocate more of their land to legumes. Component 2 (17.1%) mainly reflects management intensity and age, with the number of intensification options (0.82) and the age of the household head (0.63) loading positively. Component 3 (13.5%) contrasts the number of sustainable practices (0.57) with age (−0.59) and livestock holdings (−0.50), that is, younger households with fewer livestock that adopt more sustainable practices. Component 4 (11.2%) is defined mainly by the number of sustainable practices (0.58), indicating practice adoption that is independent of the other gradients. Along these gradients, HRE farms lie at the high end of Component 1, whereas RCM farms lie at its low end, with small landholdings and low income and livestock holdings.

Table 2. Principal component loadings for typology variables (retained components 1–4).

Variable	Comp1	Comp2	Comp3	Comp4
Age	0.099	0.634	−0.594	−0.146
Household income	0.826	−0.299	−0.250	0.049
% income from farm	−0.572	−0.349	−0.256	0.476
TLU (livestock units)	0.668	−0.104	−0.503	0.149
Total land	0.790	0.074	0.307	−0.250

Table 2. *Cont.*

Variable	Comp1	Comp2	Comp3	Comp4
Avg maize production (kg per farm)	0.692	−0.199	−0.169	0.415
% legume area	−0.547	0.393	−0.180	0.375
Count of intensification options	0.325	0.818	0.061	0.140
Count of sustainable practices	0.374	0.220	0.566	0.580

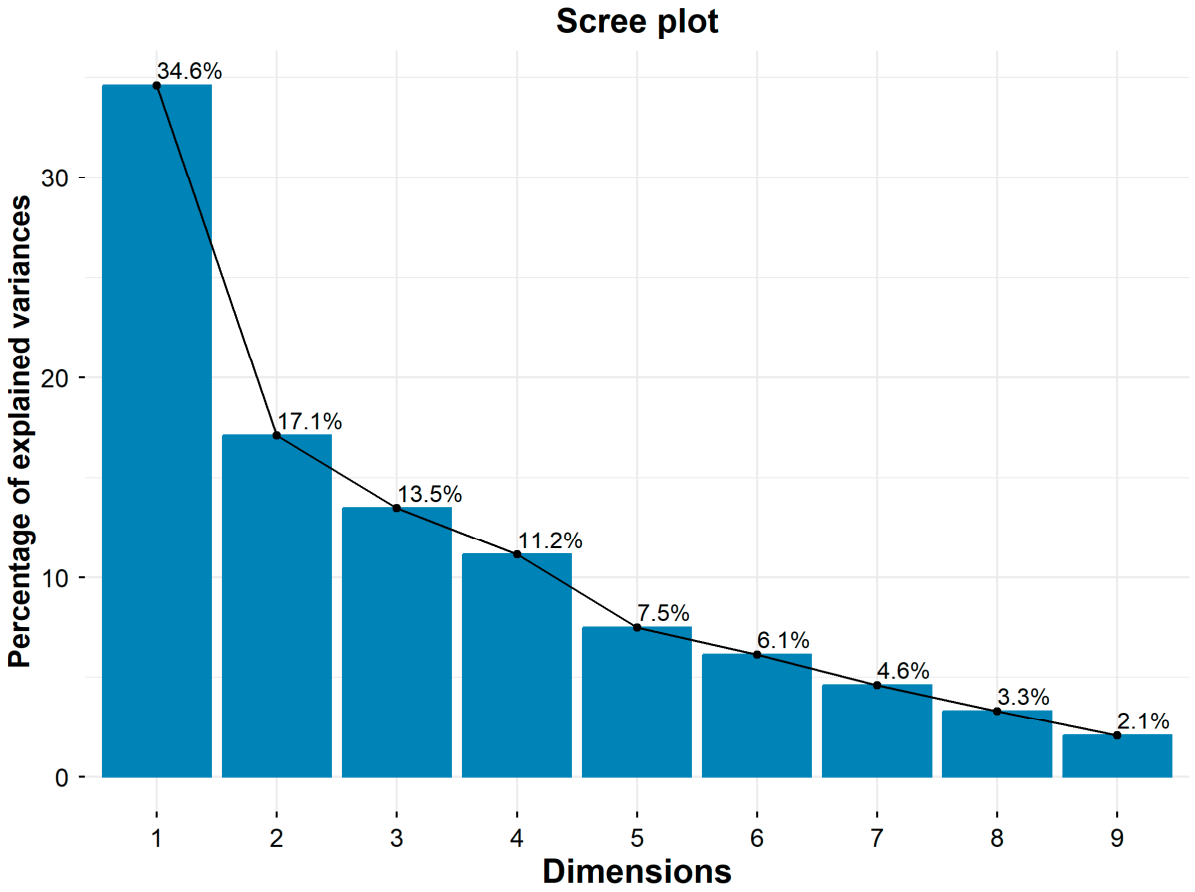


Figure 2. Scree plot showing the percentage of variance explained by each principal component; the first four components (eigenvalues 3.11, 1.54, 1.21 and 1.00, all greater than one) were retained and together explain 76.4% of the total variance.

3.2.2. Cluster Analysis and Farm Types

Cluster analysis identified four distinct farm types among the 43 surveyed households, reflecting differences in resource endowment, productivity, and management strategies. The typology is further supported by the principal component analysis (Section 3.2.1), which revealed underlying gradients in wealth and scale, management intensity and sustainable practice adoption. The fusion coefficient plot showed a relatively gradual rise in merge heights from 8.05 (five to four clusters) to 8.62 (four to three clusters) and 8.67 (three to two clusters), with the largest increase at the final merge from two clusters to one (8.67 to 13.40, a 55% increase), rather than a sharp elbow uniquely at four clusters. Average silhouette widths for the four clusters were 0.256, 0.327, 0.075, and 0.047, respectively, indicating that internal cohesion was acceptable to borderline for two clusters but weak for the remaining two when judged against the conventional 0.3 threshold. The four-cluster solution was

nonetheless retained over the statistically indicated two-cluster split because it aligned more closely with the qualitative distinctions identified in the FGDs and offered greater interpretive and targeting utility, consistent with typology development approaches that combine statistical and substantive criteria [9,10,13]; the weaker cohesion of two of the four clusters is acknowledged as a limitation in Section 4.6.

The four farm types are High-Resource-Endowed farms (HRE; 7% of the sample, $n = 3$), Moderately resource-endowed farms with Diversified Cropping systems (MDV; 14%, $n = 6$), Moderately resource-endowed farms with Mixed crop-livestock orientation (MCL; 47%, i = 20) and Resource-Constrained Maize-dominated farms (RCM; 33%, $n = 14$). Their characteristics are described in Section 3.3.

3.3. Characteristics of the Farm Types

Table 3 shows that farm types differed in resource endowment, production and practice indicators. HRE comprised only three farms, so differences involving HRE should be read with caution; the statistical tests are reported later in this section. HRE farms ($n = 3$) had numerically the highest household income (USD 2717), the largest landholdings (16.33 acres) and the most livestock (1.92 TLU), but the lowest legume area share (16%) and the smallest share of household income from farming (52.0%). RCM farms ($n = 14$) had the smallest landholdings (4.38 acres), the lowest income (USD 426), the oldest household heads (50.9 years), the highest legume area share (51.5%) and the fewest sustainable practices (1.93). MDV farms ($n = 6$) had intermediate land (6.83 acres) and income (USD 766) and the most sustainable practices (4.67). MCL farms ($n = 20$) had the youngest household heads (40.4 years), the least livestock (0.24 TLU) and the fewest intensification options (0.70).

Table 3. Socio-economic and production characteristics of farm types.

Variable	HRE	MDV	MCL	RCM	*p*-Value
Age (Mean years)	45.7 ^{ab}	44.2 ^{ab}	40.4 ^{b}	50.9 ^{a}	<0.001
Household income (USD)	2717 ^{ab}	766 ^{a}	615 ^{ab}	426 ^{b}	0.045
Share of income from farming (%)	52.0 ^{b}	86.2 ^{ab}	92.5 ^{a}	82.6 ^{ab}	0.011
Livestock ownership (TLU)	1.92 ^{ab}	0.92 ^{a}	0.24 ^{b}	0.53 ^{ab}	0.033
Farm area (acres)	16.33 ^{a}	6.83 ^{a}	4.70 ^{a}	4.38 ^{a}	0.072
Maize production, survey (kg per farm)	6000 ^{a}	4771 ^{a}	1823 ^{a}	1638 ^{a}	0.103
Maize yield, survey (kg/acre)	1145 ^{a}	1624 ^{a}	948 ^{a}	816 ^{a}	0.176
Mean maize yield, on-farm trials (kg/ha)	1415 ^{ab}	1153 ^{b}	1325 ^{b}	2046 ^{a}	<0.001
Mean legume area share (%)	16.0 ^{b}	37.3 ^{ab}	39.4 ^{ab}	51.5 ^{a}	0.002
Intensification options (count)	2.00 ^{ab}	2.00 ^{a}	0.70 ^{b}	1.79 ^{a}	<0.001
Sustainable practices (count)	3.00 ^{ab}	4.67 ^{a}	2.25 ^{b}	1.93 ^{b}	<0.001

Note: Means sharing the same superscript letter are not significantly different at $p < 0.05$. Letters come from Tukey's HSD (age, legume area share, sustainable practices, trial maize yield), Games–Howell (income, livestock, farm area, survey maize production and yield) or Holm-adjusted Dunn tests (share of income from farming, intensification options); *p*-values are from the overall test (tests are reported later in this section). Because the farm types were derived from several of these variables, the tests are descriptive. Income was converted at 1 USD = 1840 Malawi Kwacha. Survey maize production is the farmer-reported maize harvest per farm; survey maize yield is that production divided by maize area (total land multiplied by the share of land under maize). Mean maize yield is the farm mean of the on-farm trial yields (mean of the two seasonal means; first-season rotation plots, which served only as baseline, excluded); trial-name information was missing for 9 farmers (HRE 1, MDV 2, MCL 3, RCM 3), so the trial yield row is based on 34 of the 43 farms (HRE 2, MDV 4, MCL 17, RCM 11). All other variables are survey data for all 43 farms (HRE 3, MDV 6, MCL 20, RCM 14).

The most striking pattern is the decoupling between resource endowment and productivity: RCM farms, despite being the most resource-constrained, recorded the highest maize yields in the on-farm trials (2046 kg/ha), while HRE farms, with the largest landholdings and highest incomes, did not lead in trial yields. Farmer-reported maize production per farm was highest in HRE (6000 kg) and MDV (4771 kg), which largely reflects farm size. Per acre of maize, MDV was highest (1624 kg/acre) and RCM lowest (816 kg/acre). These differences are tested later in this section.

The distribution of education level (Table 4) shows that primary education was most common in RCM (78.6%), secondary education in MCL (60.0%), and MDV was evenly split between the two (50.0% each), while HRE households were spread equally across primary, secondary and tertiary education (33.3% each); tertiary education occurred only in HRE. Education level was associated with farm type (permutation chi-square test, $p = 0.04$), although group sizes are small and this should be interpreted cautiously.

Table 4. Education level of household heads across farm types (%).

Education Level	HRE	MCL	MDV	RCM	Total
None	0.00%	5.00%	0.00%	0.00%	2.30%
Primary	33.30%	35.00%	50.00%	78.60%	51.20%
Secondary	33.30%	60.00%	50.00%	21.40%	44.20%
Tertiary	33.30%	0.00%	0.00%	0.00%	2.30%

Differences among the four farm types were tested for each variable in Table 3, following the procedure in Section 2.4.2; the results are summarised in Table 5. Because most of these characteristics were also used to form the clusters, the tests are descriptive; trial maize yield, which was not used in the clustering, is the exception. With only three HRE farms (two in the trial data), non-significant results involving HRE are inconclusive.

Table 5. Statistical comparison of socio-economic and production characteristics among farm types.

Variable	Test	Statistic (df)	*p*-Value	Significant Pairwise Differences (Adjusted *p*)
Age of household head	ANOVA, Tukey	$F(3, 39) = 9.88$	<0.001	RCM > MCL (<0.001)
Household income	Welch, Games–Howell	$F(3, 8.05) = 4.24$	0.045	MDV > RCM (0.043)
Share of income from farming	Kruskal–Wallis, Dunn (Holm)	$H(3) = 11.10$	0.011	MCL > HRE (0.026)
Livestock (TLU)	Welch, Games–Howell	$F(3, 7.10) = 5.22$	0.033	MDV > MCL (0.021)
Farm area	Welch, Games–Howell	$F(3, 7.13) = 3.61$	0.072	None
Maize production, survey (kg per farm)	Welch, Games–Howell	$F(3, 6.93) = 3.04$	0.103	None
Maize yield, survey (kg/acre)	Welch, Games–Howell	$F(3, 9.17) = 2.05$	0.176	None

Table 5. *Cont.*

Variable	Test	Statistic (df)	*p*-Value	Significant Pairwise Differences (Adjusted *p*)
Maize yield, on-farm trials (kg/ha)	ANOVA, Tukey	$F(3, 30) = 9.09$	<0.001	RCM > MCL (<0.001); RCM > MDV (0.003)
Legume area share	ANOVA, Tukey	$F(3, 39) = 5.76$	0.002	RCM > HRE (0.002)
Intensification options	Kruskal–Wallis, Dunn (Holm)	$H(3) = 19.40$	<0.001	MDV > MCL (0.010); RCM > MCL (0.001)
Sustainable practices	ANOVA, Tukey	$F(3, 39) = 8.35$	<0.001	MDV > MCL (<0.001); MDV > RCM (<0.001)

Note: Test choice followed residual diagnostics (Shapiro–Wilk, Levene): Tukey's HSD where both held; Welch's ANOVA with Games–Howell where they failed; Kruskal–Wallis with Holm-adjusted Dunn tests for share of income from farming and intensification options (non-normal residuals). Survey maize yield per acre was tested with Welch's ANOVA directly. Only significant pairwise differences (adjusted $p < 0.05$) are listed, and ">" marks the type with the higher mean (or mean rank). No correction was applied across variables, so the income ($p = 0.045$) and livestock ($p = 0.033$) results are borderline. Trial maize yield is based on 34 of 43 farms (HRE 2, MDV 4, MCL 17, RCM 11); all other variables use all 43 farms (HRE 3, MDV 6, MCL 20, RCM 14).

Landholding did not differ significantly among farm types (Welch $F[3, 7.13] = 3.61$, $p = 0.072$), although HRE farms were numerically about 2.4 to 3.7 times larger than the other types (16.33 vs. 4.38 to 6.83 acres). Household income differed (Welch $F[3, 8.05] = 4.24$, $p = 0.045$), but the only significant pairwise difference was MDV above RCM ($p = 0.043$); the higher mean income of HRE (USD 2717.39) was not significantly different from any other type. Livestock ownership also differed (Welch $F[3, 7.10] = 5.22$, $p = 0.033$), with MDV (0.92 TLU) holding significantly more than MCL (0.24 TLU; $p = 0.021$) and no other pair differing. The share of household income from farming differed (Kruskal–Wallis $H[3] = 11.1$, $p = 0.011$), with HRE households relying less on farming than MCL households (52.0% vs. 92.5%; $p = 0.026$). Household head age also differed ($F[3, 39] = 9.88$, $p < 0.001$), with RCM household heads significantly older than MCL household heads (Tukey HSD, $p < 0.001$) and no other pairwise difference.

Survey-reported maize production did not differ significantly among farm types, whether expressed per farm (Welch $F[3, 6.93] = 3.04$, $p = 0.103$) or per acre of maize (Welch $F[3, 9.17] = 2.05$, $p = 0.176$). In contrast, maize yield measured in the on-farm trials (farm mean of the two seasonal means across all maize treatments, excluding the first-season baseline rotation plots; 34 of the 43 farms, because trial-name information was missing for 9 farmers: HRE 2, MCL 17, MDV 4, RCM 11) differed among farm types ($F[3, 30] = 9.09$, $p < 0.001$), and post hoc comparisons show that RCM achieved significantly higher trial yields than both MCL ($p < 0.001$) and MDV ($p = 0.003$). The difference between RCM and HRE was not significant ($p = 0.181$), but only two HRE farms had trial records, so this comparison is inconclusive, and no significant differences were observed among HRE, MCL and MDV. Games–Howell comparisons, which do not assume equal variances, gave the same pairwise result (RCM vs. MCL, $p = 0.004$; RCM vs. MDV, $p = 0.006$), although the Welch omnibus test was marginal ($p = 0.063$) because of the very small HRE and MDV groups. This highlights RCM as the most productive group in maize in the on-farm trials, despite its relatively lower resource endowment. Despite these yield differences, household income was not higher in RCM: its mean (USD 426.63) was the lowest of the four types and differed significantly only from MDV. This divergence indicates that higher maize productivity does not necessarily translate into higher overall income across farm types. Income differences may reflect broader resource endowment factors, including landholding

size and livestock ownership, as well as engagement in higher-value enterprises, but these were not tested against income here. These findings suggest that productivity and income are associated with farm typology, but not directly aligned at the individual variable level.

For sustainable practice adoption, the number of practices differed among farm types ($F[3, 39] = 8.35$, $p < 0.001$), with MDV adopting significantly more sustainable practices than both MCL ($p < 0.001$) and RCM ($p < 0.001$). No significant differences were observed between MDV and HRE ($p = 0.204$), or among the remaining groups. This reinforces the characterisation of MDV as the most sustainability-oriented system. The number of intensification options also differed (Kruskal–Wallis $H[3] = 19.4$, $p < 0.001$), with MCL using fewer options than both MDV ($p = 0.010$) and RCM ($p = 0.001$). Legume area share differed among farm types ($F[3, 39] = 5.76$, $p = 0.002$), but the only significant pairwise difference was RCM above HRE (51.5% vs. 16.0%; $p = 0.002$), so the larger legume share in RCM is supported statistically only against HRE.

Overall, the clearest differences among farm types were in on-farm trial maize yield (highest in RCM), the number of sustainable practices and intensification options, legume area share and the age of the household head. Differences in household income, livestock and the share of income from farming were weaker and involved only single pairs of farm types, whereas landholding and survey-reported maize production did not differ significantly. Education also differed, mainly between MCL (more secondary) and RCM (more primary).

To facilitate a visual comparison of farm characteristics, key variables related to productivity and resource use were standardised (scaled from 0 to 1) and presented using a radar plot (Figure 3). The variables included yields of major crops (lablab, maize, and cowpea), livestock density (TLU), total landholding, farm income per hectare, adoption of sustainable practices, and labour availability per unit land.

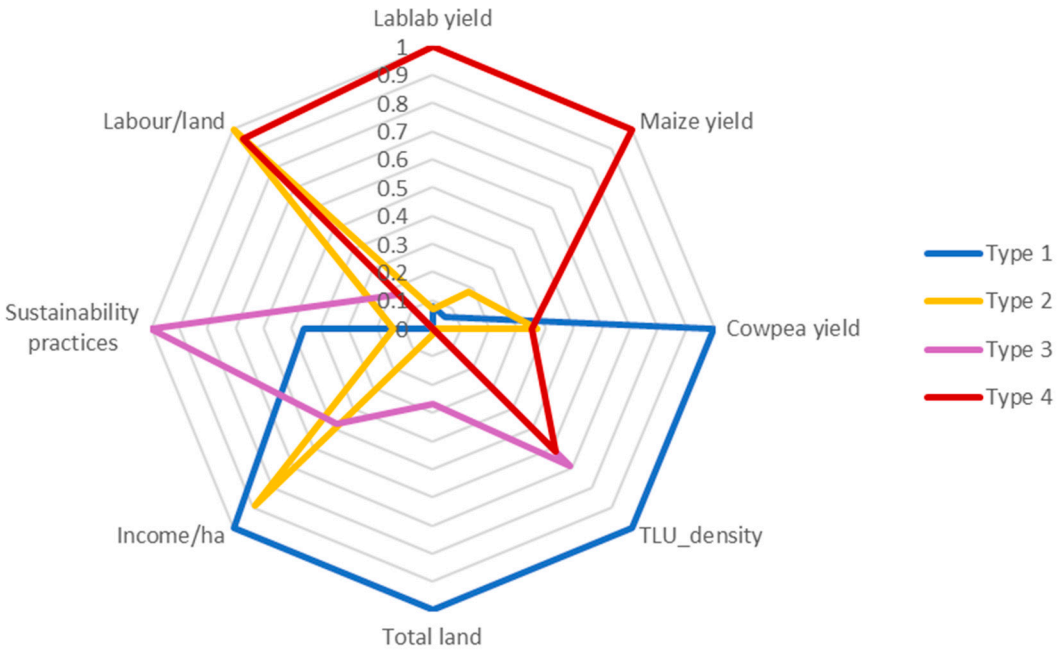


Figure 3. Radar plot showing standardised resource and production characteristics across farm types. Note. Farm types: Type 1 = HRE (High-Resource-Endowed); Type 2 = MCL (Moderately resource-endowed, Mixed crop-livestock); Type 3 = MDV (Moderately resource-endowed, Diversified Cropping systems); Type 4 = RCM (Resource-Constrained Maize-dominated).

The radar plot summarises group means and does not test differences. For several variables shown (landholding, livestock and survey-reported maize production), differences

among farm types were not statistically significant (Table 5), so the profiles below describe patterns rather than confirmed differences.

HRE emerged as the best performing group exhibiting a resource-endowed and economically strong profile, characterised by the highest values in total land, farm income per hectare, and livestock density, as well as relatively strong performance in cowpea yield. However, it showed comparatively lower labour intensity and moderate adoption of sustainable practices, suggesting a more extensive production system.

MDV displayed a balanced and sustainability-oriented profile, achieving the highest level of sustainable practice adoption while maintaining moderate levels across most other indicators, including livestock density, land size, and crop yields. This suggests a more integrated and management-intensive farming system.

MCL reflected a labour-intensive but resource-constrained system, with the highest labour-to-land ratio and relatively strong income per hectare, but generally low performance across crop yields, landholding, and livestock ownership. This indicates reliance on labour rather than asset-based intensification.

RCM demonstrated a productivity-oriented profile, with the highest maize yields among all groups in the on-farm trials (significantly higher than MCL and MDV; Table 5) and, descriptively, the highest lablab yields. However, this came alongside relatively lower farm income per hectare, limited landholding, and low adoption of sustainable practices, suggesting a focus on yield maximisation that may not yet translate into broader economic or sustainability gains.

3.4. Productivity Constraints

The focus group discussions identified a range of constraints affecting agricultural production and livelihoods in Mtunthama Extension Planning Area (EPA). These constraints were grouped into productivity, environmental, economic, institutional, and nutritional domains (Table 6).

Table 6. Agricultural constraints identified during focus group discussions in Mtunthama EPA.

Domain	Key Constraints	Illustrative Description
Productivity	Limited fertiliser access; recycled seeds; high input costs; limited improved livestock breeds	Farmers reported difficulty purchasing fertiliser and certified seed, reducing yields
Environment	Unreliable rainfall; soil erosion; deforestation	Erratic rainfall reduced crop productivity
Profitability	Poor market prices; lack of capital	Farmers reported selling crops at low prices
Social/Institutional	Limited extension services; weak group leadership	Extension coverage reported to be limited
Human/Nutrition	Poor dietary diversity; limited consumption of livestock products	Households prioritised crop sales over consumption

Limited access to inorganic fertilisers and reliance on recycled seeds were frequently reported constraints affecting crop productivity. Farmers reported that high input costs and transport expenses reduced their ability to purchase certified seed and fertiliser. Livestock production was constrained by shortages of feed, limited access to improved breeding stock, and disease outbreaks such as African swine fever and Newcastle disease.

Environmental challenges included unreliable rainfall patterns, soil erosion, and deforestation. Farmers reported late onset and early cessation of rains, which affected crop planning and yields.

Economic constraints included poor market prices, limited access to capital, and weak market linkages. Farmers indicated that crops were often sold to vendors at low prices due to lack of organised markets.

Institutional challenges included limited access to extension services due to a low extension officer-to-farmer ratio. However, some farmers reported accessing agricultural information through radio, television, and mobile phones.

Farmers also identified the major crop enterprises cultivated in the area and their relative importance for food security and income generation (Table 7).

Table 7. Relative importance of crop enterprises identified during focus group discussions.

Enterprise	Importance Score (1–10)	Primary Role
Maize	10	Staple food crop
Tobacco	8	Main cash crop
Livestock	7	Income diversification
Vegetables	7	Household food and income
Groundnuts	5	Secondary food and cash crop
Soybean	4	Secondary cash crop
Cassava	3	Food supplement
Sweet potatoes	3	Food supplement

3.5. Multi-Criteria Analysis of Sustainable Intensification Innovations

Sustainable intensification innovations were evaluated across the four farm types using multi-criteria analysis. Scores were calculated based on productivity potential, feasibility, economic viability, resource efficiency, and scalability.

The scaled innovation scores show clear variation across farm types. Conservation agriculture recorded the highest overall score (0.68), indicating the highest average suitability across farm types, followed by intercropping (0.54). Strip cropping had the lowest overall score (0.25), with adoption observed exclusively in MCL (Table 8). The "Average" column in Table 8 is the unweighted mean of the four farm-type scores for each innovation (for conservation agriculture, $(1 + 0 + 0.87 + 0.84)/4 = 0.68$). It therefore describes average suitability across farm types and is not a measure of how common the practice is among the 43 households, which was not assessed at household level. Strip cropping scored highest in MCL, the farm type with the highest labour-to-land ratio. A plausible reason is labour: conservation agriculture raises farm labour requirements, which are met mainly by household and not hired labour [29]; time-sensitive operations, particularly planting, limit smallholder uptake of grain-legume technologies in Malawi [30]; and legume crops generally require more labour per hectare than maize, with demand peaks at crop establishment, weeding and harvest [31]. Establishing and managing alternating strips of maize and legumes add to these peaks, so the practice is most feasible for the labour-rich MCL group, although this explanation was not tested in the present study. The low relative uptake does not indicate a lack of farmer interest: in a companion participatory study in the same EPA, maize–cowpea strip cropping received the highest overall preference score across farm types, with labour requirements and management complexity among the main barriers [32]. Because the scores are scaled across only four farm types, they are relative: a score of 0 or 1 marks the lowest or highest farm type for that innovation and does not mean that the practice was absent or universally adopted.

Table 8. MCDA scores for sustainable intensification innovations.

Innovation	HRE	MCL	MDV	RCM	Mean Across Farm Types
Conservation Agriculture (Intensification)	1.00	0.00	0.87	0.84	0.68
Intercropping	1.00	0.17	1.00	0.00	0.54
Small Livestock Integration	1.00	0.00	0.42	0.19	0.40
Legume–Maize Rotation (Cover Crop)	0.00	0.30	1.00	0.11	0.35
Strip Cropping	0.00	1.00	0.00	0.00	0.25
Overall Score	0.600	0.294	0.658	0.228	0.445

To test the robustness of the equal-weighting assumption, two alternative weighting schemes (economic-weighted and resource-use-weighted) were applied by reweighting the five SI innovations, since farm-type-by-criterion score data were not retained for a criterion-level sensitivity check (Table 9). In the economic-weighted scheme the weight of small livestock integration was raised from 0.20 to 0.40, and in the resource-use-weighted scheme the weight of legume–maize rotation was raised to 0.40 (0.15 for each of the other four innovations). Table 9 therefore shows the sensitivity of the farm-type scores to the weights of these two innovations, not to the weights of the underlying criteria.

Table 9. Composite MCDA scores by farm-type cluster under three weighting schemes.

Farm-Type Cluster	Equal Weighting	Economic-Weighted	Resource-Use-Weighted	Rank
HRE	0.600	0.700	0.450	2nd/1st/2nd
MCL	0.294	0.220	0.296	3rd/3rd/3rd
MDV	0.658	0.599	0.744	1st/2nd/1st
RCM	0.228	0.219	0.198	4th/4th/4th

Note: cluster numbers correspond to the four farm-type clusters (Cluster 1 = HRE, Cluster 2 = MCL, Cluster 3 = MDV, Cluster 4 = RCM).

MCL and RCM retained the two lowest composite scores across all three weighting schemes, confirming that these farm types consistently show the most limited uptake of sustainable intensification innovations regardless of weighting. However, the top rank was sensitive to the weighting scheme applied: MDV scored highest under equal and resource-use weighting, while HRE scored highest under economic weighting, indicating that the relative ordering of the top two farm types is not fully robust to the weighting choice, even though their status as the two best-performing farm types is.

MDV achieved the highest overall innovation score (0.66), followed by HRE (0.60), while MCL and RCM recorded lower scores of 0.29 and 0.23, respectively. HRE showed maximum adoption in intercropping, livestock integration, and conservation agriculture, whereas MDV demonstrated consistently high scores across multiple innovations, including rotation and conservation agriculture. In contrast, MCL relied primarily on strip cropping, while RCM showed generally low adoption across most innovations.

4. Discussion

Integrating legumes into cropping systems through practices such as crop rotation, intercropping, and conservation agriculture is widely recognised as a pathway toward sustainable intensification. These practices can improve soil fertility, enhance land-use efficiency, and contribute to more resilient farming systems when appropriately matched to local conditions [8,21–23,33]. However, the results of this study highlight that the benefits and adoption of such practices are not uniform across farm households, but instead vary

systematically with underlying differences in resource endowment, production strategies, and management capacity. This reinforces the broader understanding that smallholder farming systems are highly heterogeneous, and that uniform agricultural interventions often fail to capture this complexity [9–11,13].

4.1. Farm Diversity and Its Implications for Agricultural Development

The findings emphasise that farm diversity in Mtunthama EPA is not merely descriptive but has important implications for agricultural development planning. While the results clearly show variation in resource endowment and production strategies, the key insight is that such diversity fundamentally shapes how farmers respond to interventions and opportunities. This reinforces the argument that agricultural development approaches must move beyond aggregate recommendations and instead account for differences in capacity, incentives, and constraints across farm types [4,9,10,19].

An important implication emerging from this study is that similar external constraints such as input access limitations or climate variability do not translate into uniform outcomes across households. Rather, farm-level responses are mediated by underlying structural characteristics, particularly access to land, livestock, and labour. This highlights the risk of overgeneralising smallholder systems and supports growing evidence that heterogeneity is a defining feature of African farming systems, requiring differentiated analytical and policy approaches [10,13].

Furthermore, the observed distribution of farm types suggests that development strategies targeting only high-performing or highly resource-endowed farms may have limited impact at the population level. Instead, greater emphasis is needed on designing interventions that are inclusive of resource-constrained households, which constitute a substantial proportion of the farming population. This strengthens the case for typology-based targeting as a practical framework for improving the relevance, equity, and effectiveness of sustainable intensification efforts.

4.2. Resource Endowment and Farm Performance Patterns

The differences observed across farm types highlight the important, but not uniform, role of resource endowment in shaping farm performance. Consistent with the typology results, HRE is characterised by numerically larger landholdings and higher livestock ownership (although, with only three HRE farms, landholding did not differ significantly among farm types and, for livestock, only MDV and MCL differed significantly; Section 3.3), while MCL and RCM operate under more constrained resource conditions. These structural differences align with broader evidence that access to land and livestock assets remains a key determinant of production opportunities in smallholder systems [4].

However, the findings also demonstrate that resource endowment does not translate linearly into productivity outcomes. While HRE has the highest mean income and asset ownership (although its income did not differ significantly from that of the other types), it does not achieve the highest maize yields in the on-farm trials. Instead, RCM records significantly higher trial maize yields than MCL and MDV despite having relatively limited land and lower income levels. This suggests that farm performance reflects multiple interacting factors beyond resource access alone, including management strategies, crop choices, and possibly differential allocation of labour and inputs. Similar patterns have been reported in smallholder systems where yield outcomes are shaped by both resource availability and management intensity [4,19].

Livestock ownership remains an important distinguishing feature across farm types, particularly in differentiating wealthier households. Its contribution in this context appears to be more closely associated with income diversification and asset accumulation rather

than directly observable yield differences. While integrated crop–livestock systems are widely recognised for their role in enhancing soil fertility and resource cycling [4], the results do not show a clear yield benefit: livestock holdings were positively correlated with farmer-reported maize production per farm (Pearson r = 0.47, $p = 0.002$; Spearman ρ = 0.34, $p = 0.025$) but this largely reflects farm size, because the correlation with production per acre of maize was not significant (Pearson r = 0.22, $p = 0.16$; Spearman ρ = 0.24, $p = 0.12$) and there was no correlation with on-farm trial yield (r = −0.18, $p = 0.30$, n = 34). This reinforces the need to interpret livestock integration as part of a broader livelihood and system resilience strategy rather than a direct driver of crop yield in isolation.

The role of labour and input use also appears more complex than a simple intensification gradient. Although labour-to-land ratios differ across farm types, correlation analysis indicates a negative relationship between labour intensity and land size, suggesting that smaller farms rely more heavily on family labour. However, this does not consistently translate into higher productivity. Similarly, differences in resource endowment are not directly reflected in maize yield differences across all groups. These findings highlight that constraints in input access and labour allocation interact with other structural and management factors, reinforcing the need for context-specific interpretations of farm performance.

4.3. Implications for Targeting Sustainable Intensification Innovations

The multi-criteria analysis demonstrates that the suitability of sustainable intensification innovations as perceived by farmers varied considerably across farm types. Rather than identifying a single dominant innovation, the results suggest that innovation outcomes are strongly conditioned by farm-specific resource endowments and management strategies. This supports the argument that typology-based targeting is essential for designing effective interventions in heterogeneous smallholder systems [11,25,27].

Among the evaluated innovations, conservation agriculture and intercropping emerged as the most consistently adopted practices across farm types, indicating their relative adaptability within the study context. Conservation agriculture recorded the highest overall score, suggesting broad relevance, while intercropping also performed strongly, particularly among certain farm types. In contrast, practices such as strip cropping and legume–maize rotation showed more limited or uneven adoption, reflecting possible constraints related to labour, knowledge, or resource requirements. These adoption patterns should not be interpreted as simple technology choices, because sustained conservation-agriculture use is shaped by changing household circumstances, incentives, and local support systems [15,34].

The variation in innovation scores across farm types further illustrates differentiated adoption pathways. HRE and MDV achieved higher overall innovation scores, with MDV demonstrating particularly strong performance across multiple practices, consistent with its characterisation as a sustainability-oriented system. In contrast, MCL and RCM recorded lower scores, indicating more limited uptake of sustainable intensification practices. This pattern suggests that while some innovations are broadly applicable, their effective adoption is closely linked to household capacity and system characteristics.

Importantly, the results do not indicate a single innovation that performs optimally across all farm types. Instead, they highlight the need to consider trade-offs between feasibility, productivity, and resource requirements when promoting sustainable intensification practices. Similar findings have been reported in sub-Saharan Africa, where adoption of agricultural innovations is often uneven and shaped by local constraints and opportunities [15,16,35].

4.4. The Role of Typology-Based Targeting in Sustainable Intensification

The differentiated patterns observed across farm types underscore the importance of tailoring agricultural interventions to specific farm contexts. Typology-based approaches provide a structured framework for linking farm characteristics with appropriate development strategies, allowing for more precise targeting compared to uniform recommendations.

For resource-endowed farms, such as HRE, interventions may focus on improving efficiency and sustainability within existing production systems. Given their greater access to land and assets, these households may be better positioned to adopt practices that enhance long-term soil health and system resilience, including conservation agriculture and improved crop–livestock integration.

MDV represents a group with strong potential for sustainable intensification, given its relatively high adoption of sustainable practices and balanced resource base. Supporting this group through improved extension services and access to complementary inputs could further enhance both productivity and sustainability outcomes.

For more resource-constrained farm types, particularly MCL and RCM, the results suggest that interventions should prioritise feasibility and risk reduction rather than complexity. Lower adoption of innovations among these groups indicates that constraints related to labour, capital, or knowledge may limit the uptake of more demanding practices. In such contexts, simpler and more flexible approaches, such as intercropping or incremental improvements in input use, may offer more realistic pathways for enhancing productivity and resilience.

Overall, these findings reinforce the value of typology-based targeting as a means of aligning agricultural interventions with the diverse realities of smallholder farmers. By accounting for differences in resource endowment, production strategies, and innovation capacity, such approaches can improve both the relevance and effectiveness of sustainable intensification efforts.

4.5. Enabling Conditions for Sustainable Intensification

While farm-level innovations are important, broader institutional and policy environments play a critical role in enabling sustainable intensification. Collective action mechanisms, such as farmer cooperatives and producer groups, have been shown to improve market access, reduce transaction costs, and strengthen bargaining power for smallholder farmers [34,36]. In the context of Mtunthama EPA, strengthening farmer organisations could facilitate collective marketing of crops and livestock products while improving access to agricultural inputs.

Digital technologies also offer promising opportunities for enhancing agricultural advisory services. Mobile-based extension platforms can deliver timely information on weather conditions, pest management, and market prices, helping farmers make better-informed management decisions. Studies have shown that mobile-based advisory services can significantly improve productivity and resilience among smallholder farmers, particularly in areas where traditional extension services are limited [36–38]. Evidence from conservation-agriculture research in Malawi and the wider region also shows that outcomes depend strongly on management quality, seasonal conditions, and the fit between practices and farm resources [7,39,40].

Supportive policy frameworks are equally essential for promoting sustainable intensification. Agricultural policies that provide targeted input support, expand access to credit, and strengthen extension systems can help address the structural barriers faced by many smallholder farmers. Integrating typology-based approaches into policy design may also improve the effectiveness of agricultural development programmes by ensuring that interventions are tailored to different categories of farmers. Recent evidence from Malawi

further highlights the importance of coherent policy guidance, institutional collaboration, and adequate financing for conservation-agriculture implementation [41].

4.6. Study Limitations and Future Research

Although this study provides valuable insights into farm diversity and innovation targeting in Mtunthama EPA, some limitations should be acknowledged. First, the typology analysis is based on a relatively small sample of households, which may limit the generalisability of the findings beyond the study area. Second, the analysis relies partly on self-reported production data, which may introduce measurement errors or recall bias. Third, while the four-cluster solution was retained for its interpretive and qualitative alignment, average silhouette widths indicated only borderline-to-acceptable internal cohesion for two of the four clusters (0.256 and 0.327) and weak cohesion for the remaining two (0.075 and 0.047); a coarser, more statistically distinct two-cluster split was also supported by the fusion coefficients, and future work could usefully test the sensitivity of the typology and its policy implications to this alternative resolution. Fourth, the innovation scores in Table 8 are min–max scaled across only four farm types and are therefore relative, and the criterion-level scoring inputs for each innovation were not retained; the scores are consequently indicative, cannot be decomposed into criterion contributions or independently reproduced, and the expert-informed components could not be documented. Fifth, HRE comprised only three farms (two with on-farm trial records), so statistical comparisons involving HRE have very low power and non-significant results for HRE should be read as inconclusive; in addition, the farmer-reported maize variable used in the typology is a per-farm total, not a yield per unit area.

In addition, the typology represents a static snapshot of farm characteristics at a single point in time. Farming systems are dynamic, and households may transition between typologies as their resource endowments, livelihood strategies, and environmental conditions change. Understanding these transitions is important for designing development interventions that support long-term improvements in agricultural productivity and resilience.

Future research could build on this work by incorporating longitudinal data to examine how farm households evolve over time and how different interventions influence these trajectories. Expanding the sample size and geographic scope of similar studies would also help strengthen the evidence base for typology-based approaches to sustainable intensification across Malawi and other smallholder farming regions in sub-Saharan Africa.

5. Conclusions

This study applied principal component analysis, cluster analysis, and a multi-criteria assessment to characterise farm diversity in Mtunthama Extension Planning Area (EPA), identifying four distinct farm types that differ in resource endowment, production strategies, and livelihood outcomes. The findings show substantial heterogeneity among smallholder households, most clearly in the number of sustainable practices and intensification options adopted, legume area share, the age of the household head and on-farm maize yield; differences in landholding, livestock ownership and income were evident in the group means but were statistically supported only for some pairs of farm types. Importantly, the results show that resource endowment does not translate directly into productivity outcomes, as higher maize yields in the on-farm trials were observed among relatively resource-constrained farms, while the highest mean income was recorded for the most resource-endowed type (HRE, which comprised only three farms and did not differ significantly in income from the other types). The multi-criteria analysis further revealed that the performance and adoption of sustainable intensification innovations vary across farm types, with conservation agriculture and intercropping emerging as the most widely applicable practices. These

findings reinforce the need to move beyond uniform agricultural recommendations and instead recognise the complex and context-specific nature of smallholder farming systems.

More specifically, legume–maize rotation scored highest in MDV (1.00) and lowest in HRE (0.00), while strip cropping, the lowest-scoring innovation overall (0.25), was observed only in MCL. Education level also differed among farm types, with secondary education most common in MCL and primary education in RCM, although the small group sizes call for caution. Economic constraints were prominent in the focus group discussions: farmers reported poor market prices, limited access to capital and weak market linkages, and households often sold their crops to vendors at low prices because organised markets are lacking and prioritised crop sales over consumption. Improving market access and access to capital should therefore accompany the targeting of sustainable intensification options. Finally, the innovation scores were computed at the level of farm types from a sample of 43 households and should be read as indicative suitability scores rather than as household-level adoption rates.

The study demonstrates that typology-based approaches provide a practical framework for designing targeted sustainable intensification strategies that reflect the diverse realities of farming households. Resource-endowed farms are better positioned to adopt integrated and asset-intensive practices, while moderately resourced farms show potential for incremental improvements through enhanced access to inputs and extension support. In contrast, resource-constrained farms require low-cost, risk-reducing innovations that prioritise feasibility and resilience. While the analysis offers important insights, it is based on a relatively small, cross-sectional dataset and relies partly on self-reported information, which may limit generalisability. Future research could build on these findings by incorporating larger samples, longitudinal data to capture transitions between farm types, and more detailed biophysical indicators. Overall, the results highlight the importance of aligning sustainable intensification interventions with farm-specific conditions to improve adoption, productivity, and livelihood outcomes in smallholder systems.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su182111065/s1, Tables S1–S3: Sensitivity analysis of the farm-type composite scores to the weights of the five sustainable intensification innovations (weighting schemes, input scores, composite scores and ranks).

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Abbreviations

The following abbreviations are used in this manuscript:

ANOVA	Analysis of Variance
CGIAR	Consultative Group on International Agricultural Research
CIMMYT	International Maize and Wheat Improvement Center
DARS	Department of Agricultural Research Services
EPA	Extension Planning Area
FGD	Focus Group Discussion
HRE	High-Resource-Endowed (farm type)
IITA	International Institute of Tropical Agriculture
MCA	Multiple Correspondence Analysis
MCDA	Multi-Criteria Decision Analysis
MCL	Moderately Resource-Endowed farms with Mixed Crop-Livestock orientation (farm type)
MDV	Moderately Resource-Endowed farms with Diversified Cropping systems (farm type)
PCA	Principal Component Analysis
RCM	Resource-Constrained Maize-dominated (farm type)
SDG	Sustainable Development Goal
SI	Sustainable Intensification
SI-MFS	Sustainable Intensification of Mixed Farming Systems
SSA	Sub-Saharan Africa
TLU	Tropical Livestock Unit
USD	United States Dollar
WUR	Wageningen University & Research

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