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Executive Summary

The study utilises the integrated household panel data to identify strategies of agricultural diversification in Malawi, assess how household welfare varies with agricultural diversification strategies, and identify the factors associated with household participation in the various agricultural diversification strategies. Our analysis shows that there is a growing trend in diversification, evidenced by an increase in the share of households growing or keeping more than one type of crop or livestock between 2019 and 2024. While Maize remains a dominant crop, data shows a decline in the share of households growing Tobacco, primarily shifting towards the cultivation of legumes, especially Soybeans. Furthermore, the share of households engaged in livestock production has increased over the years, particularly chickens, goats, and sheep. Data also reveals a strong emergence and prevalence of integrated crop-livestock farming amongst farmers that diversify. Our analysis shows that diversification strategies involving "Tobacco and Livestock" are the most important in improving household income and dietary diversity. For household dietary diversity, the most impactful diversification strategies are "Cereals and Livestock", "Legumes and Livestock", "Tobacco and Livestock", and "Horticulture and Livestock". The results also show that the integration of livestock into the identified diversification approaches demonstrates a strong potential to simultaneously improve income and nutritional outcomes for households. Overall, the study finds that agricultural diversification is positively associated with household percapita income and household dietary diversity. Other factors that are positively associated with household income and dietary diversity include ownership of durable and agricultural assets, higher education levels, access to

credit, and land ownership. Household participation in agricultural diversification is positively associated with factors such as household head age, asset ownership, land ownership, and access to extension and credit. The study recommends that the government should promote integrated crop-livestock production as a strategy for enhancing household dietary diversity and income while also improving access to productive agricultural assets, land, extension services, and credit services to increase household participation in agricultural diversification.

1. Introduction

Agriculture is a key sector in Malawi's economy. The sector contributes about 22 percent to the country's Gross Domestic Product, generates about 80 percent of national export earnings, and employs 64 percent of the labour force (Government of Malawi, 2020; Government of Malawi, 2022). The agricultural sector also contributes to the country's food and nutritional security. Despite the country's significant potential for producing a wide range of food and cash crops, apiary, livestock, and fisheries products, the agricultural sector remains undiversified (Fatch et al., 2021a; Government of Malawi, 2020). Crop production is still predominantly dominated by Maize (the main staple food), while Tobacco remains the major source of export revenue(Fatch et al., 2021b). Tobacco alone accounted for 54.9 percent of the country's total export value (Government of Malawi, 2021). However, total land under cultivation for Tobacco has decreased over the years from 141,527 hectares in 2005 to 71,231 hectares in 2023. In contrast, the area under maize cultivation has increased over the same period from 1,513,929 hectares to 1,789,883 hectares. Similarly, the hectarage under legume production has increased over the years. For instance, the soya bean production has seen an increase in hectarage from 68,524 hectares in 2005 to 245,634 hectares in 2023. Similarly, groundnut production increased its hectarage from 248,276 hectares in 2005 to 445,540 hectares in 2023 (Government of Malawi, 2005, 2023).

The Malawi 2063 (the country's long-term vision paper), recognises the need to reduce overreliance on a few crops and calls for agriculture and trade policies that will support and incentivize farmers to diversify their farm production and switch to high-value crops, livestock, and fisheries for both domestic and export markets (Government of Malawi, 2020). Diversification is expected to lead to better nutritional status, dietary diversity, and higher farm incomes for farmers. Overall, agricultural diversification is anticipated to result in higher economic growth, expand the country's sources of export revenues, and improve resilience to shifts in global demand for traditional crops such as Tobacco, given that campaigns to reduce its use in many countries may cause a long-term decline in international tobacco demand (Fatch et al., 2021a, 2023a).

The country's first National Export Strategy (2013-2018), has called for the government and private sector to diversify the agricultural sector from its high dependence on the traditional production of Maize for food security and Tobacco for export revenue (Malawi Government, 2012). The most promising alternatives to Maize and Tobacco include a wide range of diverse crops and livestock products. These include edible nuts (e.g., groundnuts, macadamia, and cashew nuts); legumes (e.g., kidney beans, pigeon peas, and chickpeas); and oilseeds (e.g., soya, sunflower, and cotton); fruits and vegetables (e.g., mangoes); and high-value horticulture crops (e.g., berries, chilies, vanilla, and spices). The livestock sector also emerges as a significant avenue for food and revenue diversification, encompassing fish, meat, and poultry production (FAO, 2022).

While the potential benefits of diversification are widely recognised, evidence of the emergence of specific diversification strategies among farm households and their relationship with household welfare remains elusive. This research seeks to address this gap by identifying the agricultural diversification clusters and analyzing patterns of diversification, including shares of rural households that did not produce a particular crop or livestock type in both years, those that stopped producing, those that started producing, and those that continued to produce in both years. By identifying emerging diversification trends, the study findings will be helpful to policymakers in guiding the development of targeted interventions to sustain the country's diversification efforts. Furthermore, we analyse how household welfare varies across the identified agricultural diversification strategies. We also assess the factors associated with household participation in various agricultural diversification strategies.

2. Data and methodology

2.1. Data

The study utilises a two-wave Malawi Rural Agricultural Livelihood Panel Survey (MRALS) collected between 2019 and 2024. The 2019 MRALS interviewed 3,259 households from 8 districts across the three regions of Malawi (Northern region: Rumphi, Mzimba; Central region: Kasungu, Dowa, Lilongwe, Mchinji; and Southern region: Blantyre and Neno). These districts were purposively selected due to the high number of households growing Tobacco in those districts, especially in the northern and central regions. As noted earlier, Tobacco is one of the key crops being targeted to be diversified away from by the Government of Malawi.

The first wave followed a two-stage sampling design to identify the sample households. The first stage employed the Probability Proportional to Sizes (PPS) sampling technique to identify 137 enumeration areas across the 8 districts. In the second stage, households were randomly selected following a household listing, which was conducted in each enumeration area to identify all farming households in the 2018-2019 agricultural season. In each enumeration area, a total of 24 farming households were randomly selected, resulting in a total of 3,288 households. However, 3,259 interviews were completed after some replacements. The survey collected data on socio-economic and demographic characteristics, resource endowments, value chain economics, production systems, and access to infrastructure and services.

The follow-up survey in 2024 was implemented in four out of the original eight districts included in the 2019 MRALS, focusing on Mzimba, Kasungu, Mchinji, and Blantyre districts. These four districts accounted for 1,629 of the 3,259 households interviewed in 2019 MRALS, representing 50% of the total 2019 sample. Out of these 1,629 households, the 2024 MRALS aimed to re-interview 1,351 of them (i.e. 80%) due to budgetary constraints. However, a total of 1,245 out of the targeted 1,351 households from these four districts could be traced and successfully re-interviewed by 2024 MRALS, resulting in an attrition rate of 7.8% over 5 years between the 2019 and 2024 survey waves. Table 1 shows a sample distribution of households from the initial sample size in 2019 compared with the resurveyed households in 2024.

Table 1: Summary Statistics for Households by Panel Year

	2019 (wave 1)		2024 (wave 2)	
	HHs	Share	HHs	Share
Northern Region				
Mzimba	480	29.5%	363	29.2%
Central Region				
Kasungu	409	25.1%	304	24.4%
Mchinji	337	20.7%	264	21.2%
Southern Region				
Blantyre	403	24.7%	314	25.2%
Total	1,629	100.0%	1,245	100.0%

Source: MRALS data

Several factors contributed to the inability to locate and re-interview some households. Some had moved out of the community, often because they came to the districts in 2019 for temporary employment. Others migrated to other countries, such as Zambia or South Africa, for work. In some cases, only a single member had remained in the household, and that individual had passed away at the time of the survey. The 2024 MRALS survey instrument collected the same key information at the plot, household, and community levels as was collected by the 2019 MRALS.

If sample attrition in a longitudinal survey is non-random, then the resulting sample of panel households – those that were successfully re-interviewed in the second survey wave – may no longer be representative of the underlying population from which the first survey was drawn. If this is the case, the extent to which results of a particular statistical analysis using the panel sample are generalizable to the wider population of households may be diminished due to “panel attrition bias”. In the case of the 2019-2024 MRALS panel sample, there are two potential sources of panel attrition bias. The first source is the decision by the 2024 MRALS to not attempt to re-interview 20% of the 2019 sample of households from the four focus districts. The second source of panel attrition is related to the 7.8% attrition rate between the sample of 2019 households that the 2024 survey attempted to re-interview and the share that was successfully re-interviewed.

To test for panel attrition bias from the first source of attrition, a linear probability model (LPM) attrition analysis was conducted to assess whether the households that dropped out (due to the decision to follow 80% of the sample in the second wave) differed significantly from those re-interviewed in 2024, thereby evaluating the extent to which the retained sample remained representative of the farm households. The first step in this analysis is to define a binary variable that takes the value of 1 for each household that was excluded from attempts at re-interview and 0 if they were retained for follow-up in the second wave. Second, an LPM is estimated using OLS with the binary indicator of re-interview exclusion as the dependent variable and the 2019 value of all of the key variables planned for further analysis in this paper as explanatory variables.

The LPM attrition results in Table A1 in the appendix show that the two samples are broadly comparable, with no statistically significant differences for all the variables except the age of the household head, the education level of the household head, and household dietary diversity. While these differences may suggest potential attrition bias that could affect the generalizability of the findings, the overall attrition rate of 7.8% over 5 years (or 1.6% per annum) is relatively low. Consequently, we believe this level of attrition is unlikely to compromise the robustness and credibility of the study's conclusions.

2.2. Identifying agricultural diversification strategies

The study used cluster analysis to identify combinations of crops grown or livestock kept by farmers over the years. Cluster analysis is an exploratory data analysis technique that classifies observations or variables of similar characteristics. The study assumes that identified clusters represent different types of household agricultural diversification strategies. Stata's clustering analysis tools (see, $cluster$ and $clustermat$) were used to identify the agriculture diversification strategies.

Clustering approaches fall into two broad categories: partition and hierarchical clustering analysis (Milligan & Hirtle, 2013; Sreenivasulu et al., 2017). Partition methods break the observations into a distinct number of non-overlapping groups. The two most commonly used partition clustering methods are kmeans and kmedians cluster analysis. In the former, partition is based on means of observations, while in the latter approach, medians are computed to represent the group centers at each step. Under partition methods, the number of clusters is determined *a priori*. This approach has been criticised for being arbitrary, resulting in difficulties in validating the choice of clusters (Jain, 2010; Kaufman & Rousseeuw, 1990). Hierarchical clustering addresses this challenge.

Hierarchical clustering creates hierarchically related sets of clusters. Hierarchical clustering methods are generally of two types: agglomerative or divisive. Under agglomerative hierarchical clustering methods, each observation is considered as a separate group, and the closest two groups are combined into a single group. This process continues until all observations belong to the same group, creating a hierarchy of clusters. Unlike hierarchical agglomerative clustering, divisive hierarchical clustering begins by assuming that all observations belong to one group. This group is then split into two groups. One of these two groups is then split to create three groups; one of these three is then split to create four groups, and so on until all observations are in their separate groups (Kaufman & Rousseeuw, 1990).

Our study utilises agglomerative hierarchical clustering for two reasons. Firstly, instead of starting with a predetermined number of clusters, we statistically determine the number of clusters using two widely used criteria, namely the Caliński & Harabasz (1974) $\mathrm{pseudo-F}$ index and the Duda et al., (2001) $Je(2)/Je(1)$ index with associated pseudo-T-squared. The optimal number of clusters is selected based on the highest values of the $\mathrm{pseudo-F}$ index and Duda–Hart $\mathrm{Je}(2)/\mathrm{Je}(1)$ values (or smallest $\mathrm{pseudo-T-squared}$ values). Secondly, the existing analytical packages, including Stata, do not offer commands for divisive hierarchical clustering commands, thereby making agglomerative methods the practical choice for our analysis (StataCorp, 2021).

The clustering methods apply to continuous, binary, and mixed data. Our variables of interest are binary $(0,1)$, taking the values of 1 if the household grew or kept a particular crop or livestock and 0 if not. Cluster analysis identifies natural groupings of two closely related items or commonly found farming strategies employed by farmers, such as Maize and Soybean (representing farmers who grow maize and soybeans), or Maize and Livestock (representing farmers who grow maize and keep livestock), etc. We generate a categorical variable from the identified clusters, which consists of mutually exclusive cluster groups that are utilised in subsequent analysis. Various methods exist for creating links between crops, such as single linkage (considers the minimum distance between members of the units), complete linkage (considers the maximum distance between members of the units), average linkage (considers average distance of all distances of units in any two clusters), centroid linkage (considers distances between centroids of any two clusters) and wards linkage (considers minimum error sum of squares). Our study utilises average linkage clustering, which has been widely adopted in the literature due to its robustness and ability to function in different situations (Kaufman & Rousseeuw, 1990).

2.3. Econometric strategy

To estimate the relationship between the agricultural diversification clusters and our outcome variables (Household Dietary Diversity Score (HDDS) and household per capita income), we employed a panel data fixed effects model specified as follows:

$$y_{it} = \beta_1 C_{it} + \beta_2 X_{it} + \alpha_i + \epsilon_{it} \tag{1}$$

Where:

- y_{it} represents our outcome variables of interest, namely HDDS and log of real household per capita income;
- C_{it} represents the agricultural diversification cluster, a dummy or categorical variable of multiple diversification strategies;
- X_{it} represents the control variables, which are household and community-level factors known to influence the dependent variables of interest. The controls include: the household head's sex, household head age, head's highest education qualification level, durable asset index, agricultural asset index, size of land holding, access to extension services, access to credit, distance to a livestock market, distance to crop market, distance to ADMARC, distance to the boma (an administrative or district centre), distance to tarmac road, and survey year;
- β_i represents the coefficients for variables of interest;
- α_i is the time-constant unobserved heterogeneity (household-specific fixed effects);
- ϵ_{it} is an idiosyncratic error term, capturing time-varying unobserved factors not explained in the model; and
- $T = 2$, namely 2019 and 2024.

The Hausman test is conducted to help us decide between fixed-effects and random-effects models. The test yielded a significant $p - value$, indicating a significant correlation between the unobserved effects and the explanatory variables, justifying the choice of fixed effects to control for this correlation rather than random effects.

However, HDDS is a count variable, taking on values of 0 and positive discrete integers so we adjust the estimation method to account for the data generating process of the dependent variable. First, we employ the Shapiro-Wilk and Kolmogorov-Smirnov tests of normality to confirm that HDDS is not normally distributed. Next, we conduct Deviance goodness-of-fit and Pearson goodness-of-fit tests to determine whether HDDS is better suited to a Poisson or negative binomial estimator. The test results indicate that HDDS follows a Poisson distribution. Consequently, we modify Equation 1 by incorporating correlated random effects terms and relaxing the assumption that unobserved heterogeneity and explanatory variables are correlated.

To assess the correlates of agricultural diversification, we adopt the bias-reduced fixed effects (BRFE) probit approach by Kunz et al. (2021). This approach has been widely used in binary fixed effects choice modelling (Buchmueller et al., 2021; Kung et al., 2023; Kunz et al., 2024) and is suitable for our dependent variable, agriculture diversification, which takes the value of 1 if a household diversified in any of the identified cluster groups and 0 if the household did not diversify production. The BFRE approach addresses the weaknesses of the fixed effects probit model, which has been criticized for producing biased estimates due to the incidental parameters problem when N is large and T is small. BRFE addresses the incidental parameters problem, provides finite estimates for all fixed effects, and estimates them with minimal bias. The methodology also avoids the perfect prediction problem that influences the estimation of choice models. Mathematically, the BRFE model is specified as follows:

$$P(d_{it} = 1 \mid \theta_i, H_{it}) = \Phi(H_{it}\gamma + \theta_i) \tag{2}$$

Where d_{it} is household's i participation in agricultural diversification at the time t as defined above; H_{it} is a vector of independent covariates; θ_i represents unobserved household-specific fixed effects and Φ represents the cumulative distribution function of the standard normal distribution.

For robustness checks, we compute the correlated random effects model (CRE) which relaxes the assumption of no correlation between unobserved heterogeneity and explanatory variables. In the CRE model, we include the averages of all the time-varying variables as additional regressors.

2.4. Computation of asset indices, HDDS, and real household per capita income

The household dietary diversity score (HDDS) is the cumulative count of the food groups consumed by the household in the past 24 hours, reflecting the household's access to various foods. Several indicators have been developed to measure dietary diversity. In this study, we used HDDS measured as a count of the 12 food groups that have been consumed by the household in the previous 24 hours, including (1) cereals, (2) roots and tubers, (3) vegetables, (4) fruits, (5) meat, poultry, and offals, (6) eggs, (7) fish and seafood, (8) pulses, legumes, nuts, (9) milk and milk products, (10) oil, (11) sugar/honey, and (12) miscellaneous (Swindale & Bilinksy, 2006). Household income is based on respondent recall of household earnings from both agriculture and non-agricultural activities over the previous 12 months. These activities include casual labor, regular employment, and business. The household income included the value of household food crop production retained for own household consumption and all gross earnings from all income-generating activities including crop sales, casual labor, regular employment, and business from any household member in the past 12 months. The total income of the household is divided by the number of household members to obtain the household per capita income.

Two asset indices were constructed: one for durable assets and a separate index for productive assets. We use a comprehensive list of assets owned by households at the time of the surveys to construct these indices. The productive asset index is constructed using productive farm assets[1] owned by the household. This index provides a measure of a household's current productive capacity. Likewise, the durable asset index is constructed based on household ownership of durable goods related to transportation (bicycle, motorcycle, truck), housing characteristics (number of rooms, type of roof, walls, and floor), and other assets such as radios, etc. A durable asset index is often used as a proxy for household wealth. Thus, households with a higher score in either of the indices are expected to have better chances of improving their welfare in the future. We used the Stata command for multiple correspondence analysis (mca) to compute the indices (Asselin & Anh, 2008; Laderchi & Savastano, 2013; Vollmer & Alkire, 2022).

3. Results and discussion

3.1. Selected household characteristics

Table 2 shows the means of selected characteristics of panel households in 2019 and 2024. Our analysis is based on a balanced panel of 1,176 households, leaving out split-off households and households that did not engage in crop or livestock production, namely rural households not engaged in farm activities. The data shows a decrease in household per capita income from K56,836 in 2019 to K49,634 in 2024 in real terms. This decline appears to be largely a result of lower agricultural production due to the adverse effects of El Nino experienced during the 2023/24 season, which was characterised by a late onset of rains, prolonged dry spells, and floods in some areas.

[1]Farming assets included: hand hoe, slasher, axe, sprayer, panga knife, sickle, treadle pump, watering can, ox cart, ox plough, tractor, ridger, generator, motorized pump, grain mill, chicken house, livestock kraal (livestock, goats), storage house, granary, barn, pig sty, poultry kraal (other than chicken)

Table 2: Summary of Selected Socioeconomic Characteristics of Panel Households, by Year (N=1,176 in each year)

Variable	2019		2024	
	Mean	SD	Mean	SD
Real household per capita income	56 836	237 065	49 634	174 507
Household dietary diversity	2.62	1.33	2.84	2.11
Household head age	44.04	15.70	49.16	15.41
Household head is male (1=yes)	0.74	0.44	0.73	0.44
Household size	5.28	2.30	5.62	2.19
Highest level of education				
None	0.67	0.47	0.68	0.47
Primary school	0.16	0.36	0.15	0.36
Junior certificate	0.10	0.30	0.09	0.29
Secondary certificate	0.06	0.23	0.07	0.25
College Certificate	0.01	0.11	0.01	0.07
Diploma	0.01	0.08	0.00	0.06
Degree	0.00	0.04	0.00	0.06
Land owned (acres)	3.27	3.16	4.03	4.39
Durable asset index	0.12	1.14	0.08	1.07
Agricultural asset index	0.08	1.14	0.06	1.09
Access to extension (1=yes)	0.37	0.48	0.55	0.50
Access to credit (1=yes)	0.29	0.45	0.18	0.38
Distance to livestock market	13.15	13.13	9.69	11.16
Distance to crop market	11.44	12.79	8.13	8.17
Distance to ADMARC	12.51	13.26	10.64	10.87
Distance to the boma	39.52	26.79	39.07	25.42
Distance to tarmac road	12.79	14.17	13.08	16.02

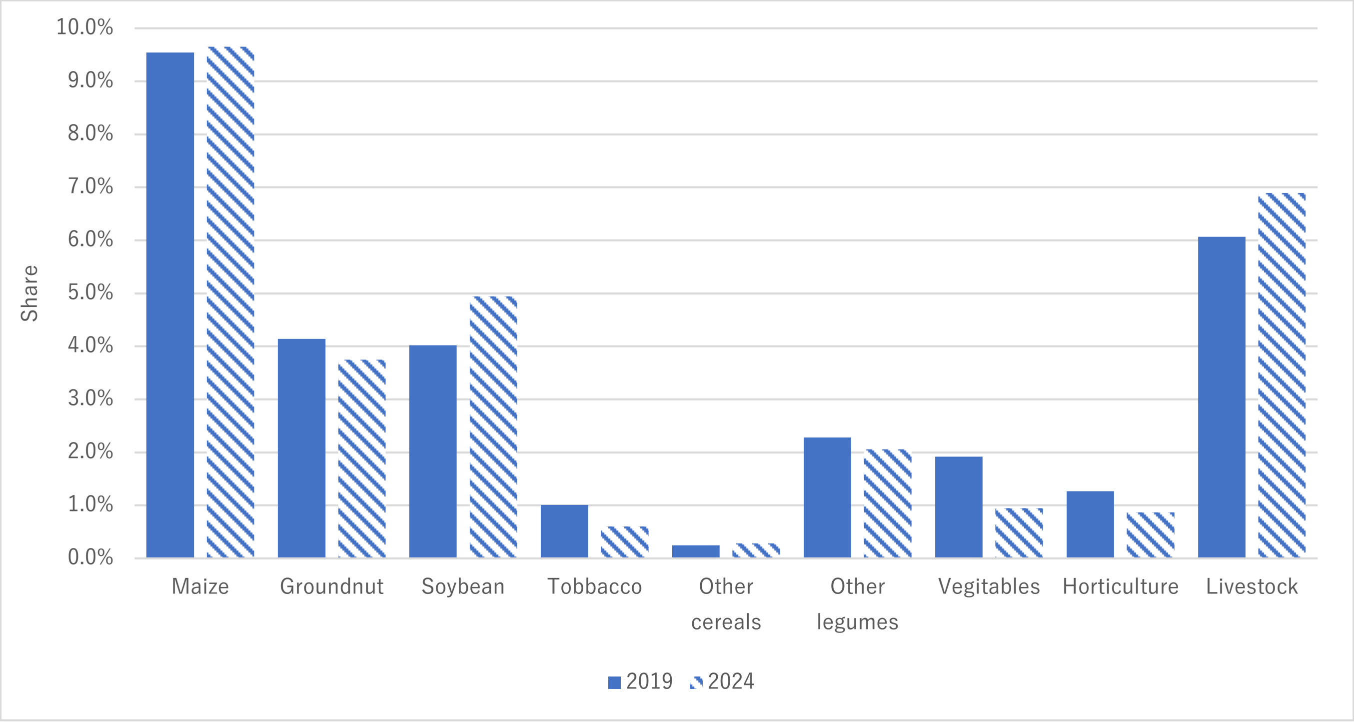
Source: Authors' analysis from 2019 and 2024 MRALS data.

The average HDDS increased from 2.62 in 2019 to 2.84 in 2024, suggesting an improvement in dietary diversity among the panel household sample. As expected, the average age of the household head has increased from 44 years to 49 years in 2024. The average levels of education remained essentially unchanged, with most household heads lacking formal education, namely 67% in 2019 and 68% in 2024. The land holding size increased from 3.3 acres to 4 acres in 2024. While there was a large increase in the share of households with access to extension services from 37% in 2019 to 55% in 2024, the share with access to credit decreased from 29% in 2019 to 18% in 2024.

3.2. Patterns of agricultural diversification

Figure 1 reveals crop production patterns between 2019 and 2024. Maize, the staple crop, remains dominant but exhibits a very slight increase from 95.4% in 2019 to 96.5% in 2024. Tobacco production has decreased significantly from 10.1% to 6.1% over the same period. Other crops, such as groundnuts, vegetables, and horticultural crops, also show declining trends. The decrease in the production of traditional crops such as Tobacco suggests diversification into alternative crops such as soybeans, which has been identified as one of the potentially viable alternatives to Tobacco as a main export crop. The share of households engaged in livestock production has increased from 60.6% in 2019 to 68.9% in 2024.

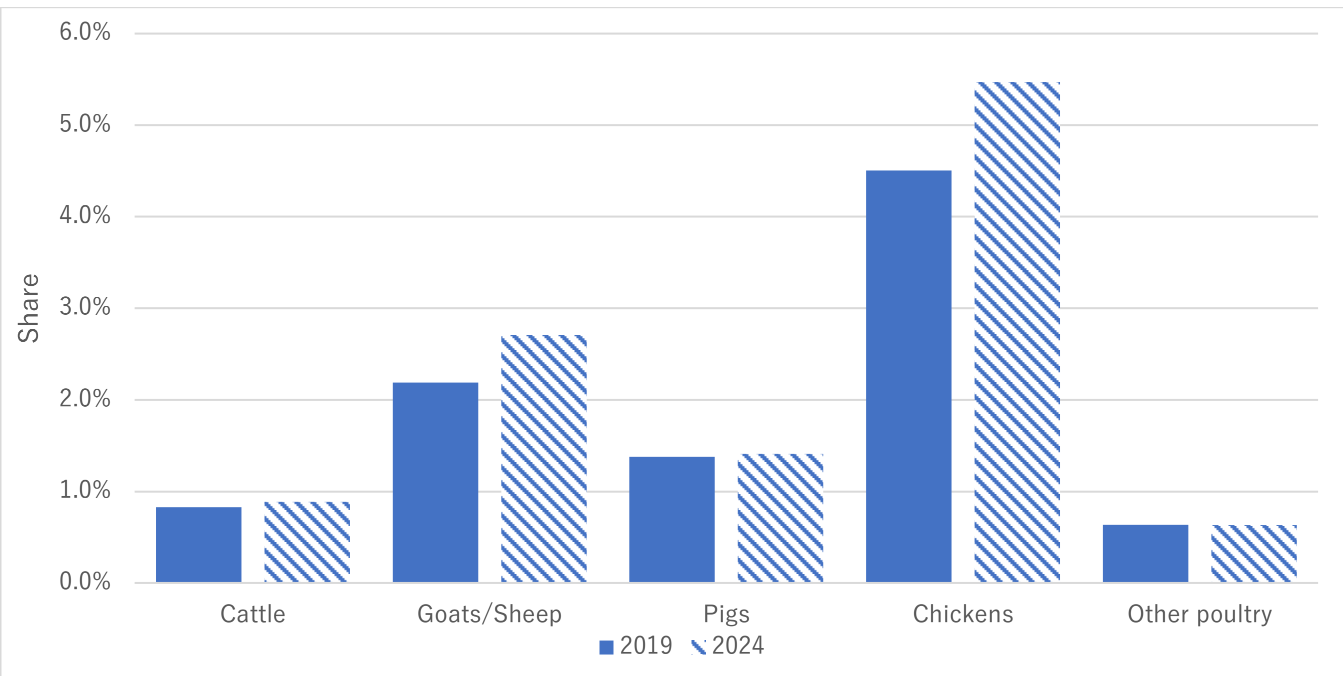
Figure 1: Shares of Households Engaging in Crop and Livestock Production, 2019 and 2024



Source: Authors' analysis of 2019 and 2024 MRALS data.

Figure 2 shows the shares of households keeping the various types of livestock in 2019 and 2024. Data shows an increase in the share of households keeping all livestock types, particularly chickens and goats/sheep whose shares increased from 45.0% of households in 2019 to 52.9% in 2024 and 20.9% in 2019 to 25.9% in 2024, respectively. The increase in the share of households keeping chickens and goats/sheep is possibly due to the livestock goat pass-on programs that target these particular animals, which the Government of Malawi has implemented in partnership with several development partners such as the International Fund for Agricultural Development. The share of households keeping cattle, pigs, and other poultry increased marginally between 2019 and 2024. Other poultry includes turkeys, doves, and ducks.

Figure 2: Shares of Households Keeping Livestock, by Livestock Type, 2019 and 2024



Source: Authors' analysis of 2019 and 2024 MRALS data.

Building on the trends analyzed and observed above, we use transition matrices to examine changes in crop and livestock production between 2019 and 2024. This allows us to understand the share of households moving into and out of the production of specific crop and livestock types. The detailed results of this analysis are presented in Tables A2 and A3 in the appendix. The transitions show that maize remains the dominant crop grown by 96.68% of the majority of households in both years, followed by Soybean (70.07%) and Groundnut (52.39%). However, of the households that grew Tobacco in 2019, about 62.28% stopped growing in 2024, suggesting diversification away from this crop. Data shows about 28.05% and 23.46% of households moved into the production of Soybean and Groundnut in 2024, respectively. With respect to livestock, the dominant livestock types kept by households in both years include chickens (61.93%), cattle (58.82%), and goats/sheep (56.98%). Notably, data reveals a significant proportion of households are transitioning into chicken and goat/sheep farming compared to other types of livestock. Specifically, 45.77% of households shifted to chicken farming, while 18.66% moved into goat or sheep farming in 2024.

3.3. Crop and livestock diversification trends

Table 3 shows the shares of households engaged in crop and livestock production in 2019 and 2024. For ease of analysis, we categorised rural households into three groups: those growing no crops or keeping no livestock, those growing one crop or keeping one type of livestock, and those growing multiple crops or keeping multiple types of livestock. The maximum number of crops grown or livestock kept was 9.

Table 3: Shares of Households Engaged in Crop and Livestock Production between 2019 and 2024

	Crop production (%)		Livestock production (%)	
Number	2019	2024	2019	2024
0	1.77	1.14	39.36	31.14
1	16.61	21.42	24.77	24.66
2-9	81.62	77.45	35.88	44.20

Source: Authors' analysis of 2019 and 2024 MRALS data.

Data reveals several trends. The share of households not growing any crops decreased slightly from 1.77% in 2019 to 1.14% in 2024 while the share of households growing one crop increased from 16.61% in 2019 to 21.42% in 2024. Furthermore, the share of households growing more than one crop declined from 81.62% in 2019 to 77.45% in 2024. With respect to livestock production, data shows that the share of households not keeping livestock declined from 39.36% in 2019 to 31.14% in 2024. On the other hand, the share of households engaged in the production of more than one livestock type increased from 35.88% in 2019 to 44.20% in 2024. Overall, these results signal a declining trend in crop diversification while observing an increasing trend in livestock diversification, interpreted as engaging in the production of multiple crops or the rearing of multiple livestock species, rather than a single crop or livestock type.

3.4. Crop and livestock diversification clusters

Using cluster analysis, we identified mutually exclusive groups of naturally emerging closely related crops and livestock produced by households. The clusters include cereals (comprising maize, sorghum, finger millet, rice, and wheat); legumes (comprising soybean, groundnut, pigeon peas, common beans, peas, ground beans, and sunflower); horticulture (comprising vegetables and fruits); and livestock (comprising cattle, chickens, ducks, pigeons, doves, guinea fowls, turkey, donkeys, sheep, goats, rabbits, and pigs. Table 4 presents the dissimilarity coefficients amongst cereals, legumes, tobacco, horticultural crops, and livestock production. Lower values indicate higher degrees of similarity among the listed items. For a visual representation of the cluster analysis, see Figure A1 in the appendix.

Table 4: Dissimilarity Coefficients of Crop and Livestock Production

	Cereals	Legumes	Tobacco	Horticulture	Livestock
Cereals	0				
Legumes	0.2691	0			
Tobacco	0.9222	0.9214	0		
Horticulture	0.7652	0.7741	0.9452	0	
Livestock	0.3751	0.4358	0.9081	0.7803	0

Source: Authors' analysis of 2019 and 2024 MRALS data.

The results show that cereals and legumes have the lowest dissimilarity coefficient (0.2691), indicating that these two are the most commonly paired crops among farming households. The next most common combinations are cereals and livestock (0.3751) and livestock and legumes (0.4358). These findings suggest that households tend to group certain types of crops with livestock together more frequently than with other crops, underscoring the importance of integrated crop-livestock farming, which is often associated with higher productivity and improved welfare for smallholder households.

3.5. Household welfare by agricultural diversification cluster

Building on the associations identified through cluster analysis in the preceding section, we analyse how household welfare varies across the different clusters. Specifically, we compare each cluster's average real household per capita income and HDDS against the base category (cluster 0) and then conduct t-tests to assess if the differences in household income and dietary diversity between each cluster and the base group are statistically significant. Table 5 focuses on household per capita income as an indicator of welfare.

Table 5: Results of t-tests Comparing Real Household Per capita Income Across Agricultural Diversification Clusters (for both 2019 and 2024)

Agricultural diversification cluster	Mean income	Difference	t-statistic	N
Cereals and legumes (comparison group)	32,087			402
Cereals and Livestock	25,289	6,797	1.22	219
Legumes and Horticulture	29,994	2,093	0.30	119
Legumes and Livestock	42,818	-10,731**	-2.33	778
Tobacco and Livestock	293,115	-261,028***	-5.44	113
Horticulture and Livestock	58,909	-26,822***	-4.07	372
Other clusters	64,919	-32,832***	-2.71	84

Source: Authors' analysis of 2019 and 2024 MRALS data. Note: Other clusters include "Cereals & Tobacco"; "Cereals & Horticulture" and "Legumes & Tobacco". These were grouped into "Other Clusters" due to small samples in each category.

The average real household per capita income for households in the cereals and legumes diversification strategy (comparison group) was K32,086.70. When comparing the various diversification clusters to this base group, data reveals that households in the Tobacco and Livestock diversification strategy have the highest income and significant difference. Other clusters exhibiting statistically significant higher incomes compared to the base group include "Legumes and Livestock", "Horticulture and Livestock" and "Other clusters". The results suggest that engaging in these diversification strategies is associated with substantial improvements in household welfare compared to engaging in subsistence clusters, namely the "Cereals and legumes" group.

Table 6 presents the results of t-tests for household dietary diversity scores across the various diversification clusters compared to the base group. This base group includes households who are engaged in the production of cereals and legumes. Our analysis shows that households in the "Cereals and Livestock" diversification cluster have the largest statistically significantly higher HDDS scores compared to the base group, followed by the "Tobacco and Livestock," "Horticulture and Livestock," and "Legumes and Livestock" clusters. As before, livestock production consistently features in diversification clusters associated with higher household welfare.

Table 6: Results of t-tests for Household Dietary Diversity Across Diversification Clusters

Agricultural diversification cluster	Mean HDDS	Difference	t-statistic	N
Cereals and legumes (comparison group)	2.43			402
Cereals and Livestock	2.90	0.47***	0.72	219
Legumes and Horticulture	2.24	-0.19	-0.01	119
Legumes and Livestock	2.77	0.34***	-3.46	778
Tobacco and Livestock	2.84	0.41**	1.00	113
Horticulture and Livestock	2.81	0.38***	-4.76	372
Other clusters	2.63	0.20	-2.89	84

Source: Authors' analysis of 2019 and 2024 MRALS data

3.6. Agricultural diversification and household welfare

Table 7 shows results from our fixed effects regression analysis of equation (1) based on the household outcome variables, namely the log of real household per capita income (models 1 and 2) and HDDS (models 3 and 4). Models 1 and 3 include binary indicators of agricultural diversification clusters and survey year as explanatory variables. Models 2 and 4 extend the analysis by adding other control variables. The control variables used in the analysis include household head age, age of household head squared, the sex of the household head, household head's highest level of education, durable asset index, agricultural asset index, land owned (in acres), land owned (in acres) squared, access to extension services, access to credit, distance to livestock market, distance to crop market, distance to ADMARC, distance to the boma, distance to tarmac road, and survey year. For HDDS, which is based on Poisson regression, the additional control variables include averages of all time-varying explanatory variables, as earlier discussed in the methodology.

Table 7: Relationship Between Agricultural Diversification Clusters and Real Household Per Capita Income a**Household Dietary Diversity, 2019 and 2024**

	Fixed effects (Log of per capita income)				Poisson (HDDS)			
	(1)		(2)		(3)		(4)	
Explanatory variables	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Diversification strategy								
Cereals and Livestock	-2.039***	(-5.49)	-2.126***	(-5.79)	0.177***	(3.25)	0.095*	(1.86)
Legumes and Horticulture	-0.308	(-0.69)	-0.544	(-1.26)	-0.08	(-1.36)	-0.054	(-0.98)
Legumes and Livestock	0.374	(1.40)	0.027	(0.10)	0.129***	(3.37)	0.080**	(2.15)
Tobacco and Livestock	1.689***	(3.20)	1.170**	(2.25)	0.156**	(2.19)	0.081	(1.13)
Horticulture and Livestock	0.425	(1.32)	-0.109	(-0.33)	0.144***	(3.26)	0.081*	(1.89)
Other clusters	0.209	(0.40)	0.210	(0.41	0.079	(1.00)	0.097	(1.36)
Time effects	Yes		Yes		Yes		Yes	
Controls	No		Yes		No		Yes	
N	2,087		2,087		2,087		2,087	
Prob > F/ chi2	0.000		0.000		0.000		0.000	

Source: Authors' analysis of 2019 and 2024 MRALS data; Note: Coeff represents coefficient; Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1.

The results show that for real household per capita income (models 1 and 2), the "Tobacco and Livestock" diversification strategy yields a positive and significant relationship, while the "cereals and livestock" strategy has a negative association (with and without controls) when compared to the base category of "Cereals and legumes". When HDDS is used as an outcome variable (models 3 and 4), most diversification clusters generate positive and significant associations, except for the "legumes and horticulture" and "other" diversification clusters.

The control variables with a positive relationship in model 2 (real household per capita income) include junior certificate and secondary certificate level of education for the household head age (compared to no education), durable asset index, and size of land squared. On the other hand, the age of the household head squared, the amount of land owned squared, and the distance to the boma. In model 4, control variables with a positive relationship to HDDS include the agricultural asset index and survey year. Factors with negative and significant relationships include access to extension services and distance to boma average. The negative and significant relationship between access to extension services and HHDS suggests a mismatch between extension advice and dietary diversity, given that extension advice is often focused on agricultural practices rather than nutrition.

Our results support previous evidence on the significance of agriculture diversification in enhancing dietary diversity and household income (Fatch et al., 2023b). Our results primarily reveal the idea that integrating cash crops and livestock is important for enhancing household income and dietary diversity. This is unsurprising as these links offer multiple pathways to improving household access to various foods. First, cash crops enhance household income, which improves households' purchasing power (Usman & Callo-Concha, 2021). Moreover, livestock production directly supports household food consumption by providing either meat, milk, or eggs, which may be complemented by foods purchased using incomes realised from cash crops (Jodlowski et al., 2016; Yan et al., 2024).

In addition to agricultural diversification clusters, we also find that other household characteristics, such as assets and education, play a critical role in supporting household diet diversity and income. These results are not surprising, as agricultural assets are ideal for enhancing household food productivity, which eventually improves household consumption through income or direct consumption (Ansah et al., 2022). Moreover, ownership of assets cushions households from different shocks, which ensures continuous access to diverse food (Ansah et al., 2022). Furthermore, more highly educated household heads are more likely to make informed decisions on their consumption patterns (Kabeta et al., 2023). Moreover, high education qualifications offer an excellent probability of ensuring households engage in formal employment, which eventually offers high income to purchase diverse foods (Herzberg-Druker & Stier, 2019).

3.7. Factors affecting household participation in agricultural diversification clusters

Table 8 shows the estimated average marginal effects obtained from the bias-reduced fixed effects probit model. Our dependent variable, agriculture diversification, takes the value of 1 if a household diversified in any of the identified cluster groups and 0 if a household belongs solely to the "cereal and legume" cluster. Non-farming households have been dropped from the analysis. We find that as the household age increases, the probability of the household participating in agricultural diversification also increases (Grilli et al., 2024). However, this trend has a cut-off point at which household participation in agricultural diversification starts to decline. The results also show a statistically significant and positive correlation between agricultural diversification and the level of education, ownership of durable assets and landholding. A similar relationship between household agriculture diversification and assets and land ownership was observed in Uganda (Antonelli et al., 2022). These results suggest that households with higher resource endowments are more likely to engage in agriculture diversification, unlike their counterparts. Similarly, access to various institution services, such as access to extension services and credit, significantly supports household participation in agricultural diversification (Adesiyan & Kehinde, 2024). However, the results also show a negative correlation between male-headed households (when compared to female-headed households) and agricultural diversification. Female-headed households (compared to male-headed households) face more barriers such as access to agricultural resources (land, inputs, and assets) and this may encourage them to engage in agricultural diversification to mitigate against the many challenges faced.

Table 8: Factors Affecting Household Participation in Agricultural Diversification Clusters, 2019 & 2024 Based on the Biased Reduced Fixed Effects Probit Model Estimation

Explanatory variable	Average marginal effects	Std. error
Household head is male (1=yes)	-0.062**	0.026
Household head age	0.009**	0.004
Age of household head squared	0.000	0.000
Household size	0.011**	0.004
Household head highest level of education		
Primary school	0.020	0.027
Junior certificate	0.022	0.036
Secondary certificate	0.071*	0.043
College Certificate	0.051	0.083
Diploma	0.097	0.102
Degree	-0.102	0.201
Durable asset index	0.022**	0.009
Agricultural asset index	0.011	0.009
Land owned (acres)	0.011***	0.004
Land owned (acres) squared	0.000**	0.000
Access to extension (1=yes)	0.045***	0.015
Access to credit (1=yes)	0.048***	0.018
Distance to livestock market	0.001	0.001
Distance to crop market	-0.001	0.001
Distance to ADMARC	0.000	0.001
Distance to the boma	-0.001	0.001
Distance to tarmac road	0.000	0.001
2024 survey year	-0.052***	0.012
Number of observations	2,352	

Source: Authors' analysis of 2019 and 2024 MRALS data; Note: Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1.

For robustness checks, we analysed the factors associated with a household's participation in agricultural diversification using the correlated random effects model. The results from the bias-reduced fixed effects probit model (Table 8) and random correlated effects (see Table A4 in the appendix) are very similar in sign and magnitude. Specifically, just as before, we find that the factors positively associated with agricultural diversification include being a male household head, education (primary school and college certificate compared to the base category of no education), durable asset index, agricultural asset index, land ownership, land ownership squared, access to extension services, and access to credit. Explanatory variables with negative associations with agricultural diversification include the age of the household head, household size, distance to distances to the boma, and distance to a tarmac road.

4. Conclusions and recommendations

Agriculture diversification has been identified as a potential means to increase household food security and household income, and the government of Malawi has made efforts in recent years to promote agricultural diversification. However, there is limited evidence from Malawi of specific types of household agricultural diversification strategies used by farm households and which strategies are more likely to be associated with improvements in household food security and income. In this study, we addressed this gap by first identifying patterns in agricultural diversification among rural households in Malawi and defining the predominant agricultural diversification strategies used. Second, we analyse the extent to which household food security and total household farm income vary across particular agriculture diversification strategies. Third, the study identifies the diversification strategies or patterns that are the most important for income generation and enhancing household dietary diversity. Fourth, we assess the factors associated with household participation in specific agricultural diversification strategies.

The study found mixed results in the patterns of agriculture diversification. Primarily, we observe a growth in household participation in clusters that incorporate food crops and cash crops, food crops and livestock, or cash crops and livestock. Furthermore, our results identify these cluster combinations as the most critical in enhancing household dietary diversity and incomes. In addition to the identification of these clusters, we find that other socio-economic and institutional factors, such as the age of the household head, assets, access to extension services, credit, and land ownership, are positively associated with household participation in agricultural diversification.

Based on the findings, we recommend that efforts to enhance agriculture diversification should focus on promoting crop-livestock production as a strategy for enhancing household dietary diversity and income. Furthermore, strategies to enhance diversification should focus on improving households' access to productive agricultural assets and land, as well as extension services and credit services. Lastly, interventions aimed at enhancing diversification should target households based on their characteristics to accelerate the adoption of agricultural diversification.

5. Study limitations

First, our study coverage is limited to four districts in Central and Northern Malawi where tobacco cultivation has been prominent, which may limit its external validity. Additionally, the study period has been affected by a series of climate-related weather shocks, which would significantly affect the results if the conditions were similar.

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Appendices

Table A1: Comparison of Baseline Characteristics between Households that were not Followed in the Second Wave and those that were Resurveyed

Description	Coefficient	t-stat
Household dietary diversity	-0.020**	(-2.24)
Log of real household per capita income	-0.002	(-0.58)
Household head is male (1=yes)	0.004	-0.15
Age of household head	0.010**	-2.53
Age of household head squared	-0.000**	(-1.97)
Highest education		
Primary school	-0.013	(-0.42)
Junior certificate	0.015	-0.39
Secondary certificate	-0.082*	(-1.76)
College Certificate	-0.047	(-0.54)
Diploma	-0.041	(-0.30)
Degree	-0.035	(-0.14)
Durable asset index	-0.016	(-1.46)
Agricultural asset index	0.018	-1.44
Log of land owned (acres)	0.013	-0.81
Access to extension (1=yes)	0.000	(-0.02)
Access to credit (1=yes)	0.038	-1.53
Constant	1.542***	-15.15
R-squared	0.024	
No. of observations	1572	

Source: Authors' analysis of 2019 and 2024 MRALS data

Table A2: Crop Production Changes between 2019 and 2024

Description		Crop transitions		
Crop Type		0	1	Total
Maize	0	8.89	91.11	100
	1	3.09	96.91	100
	Total	3.32	96.68	100
Groundnut	0	76.54	23.46	100
	1	47.61	52.39	100
	Total	65.22	34.78	100
Soybean	0	71.95	28.05	100
	1	29.93	70.07	100
	Total	56.55	43.45	100
Tobacco	0	97.55	2.45	100
	1	62.28	37.72	100
	Total	94.43	5.87	100
Other cereals	0	96.92	3.08	100
	1	72.50	27.50	100
	Total	96.09	3.91	100
Other legumes	0	85.54	14.46	100
	1	53.18	46.82	100
	Total	76.02	23.98	100
Vegetables	0	92.33	7.67	100
	1	83.20	16.80	100
	Total	90.39	9.61	100
Horticultural crops	0	92.47	7.53	100
	1	84.42	15.58	100
	Total	91.41	8.59	100

Source: Authors' analysis of 2019 and 2024 MRALS data

Notes:

a. Other Cereals include sorghum, finger millet, rice, and wheat.
b. Other Legumes include pigeon peas, common beans, peas, ground beans, and sunflower.
c. Vegetables include cabbage, leafy vegetables, okra (therere), tomato, and onion.
d. Horticultural crops include sweet potato, potato, banana, guava, and pineapple.

Table A3: Livestock Production Changes between 2019 and 2024

Description		Livestock transitions		
Livestock type		0	1	Total
Cattle	0	95.6	4.40	100
	1	41.18	58.82	100
	Total	91.67	8.33	100
Goats/Sheep	0	81.34	18.66	100
	1	43.02	56.98	100
	Total	72.70	27.30	100
Pigs	0	90.80	9.20	100
	1	62.99	37.01	100
	Total	87.16	12.84	100
Chickens	0	54.23	45.77	100
	1	38.07	61.93	100
	Total	46.68	53.32	100
Other poultry	0	95.42	4.58	100
	1	74.12	25.88	100
	Total	93.88	6.12	100

Source: Authors' analysis of 2019 and 2024 MRALS data. Note: Cattle includes Calves, Cows, Bulls, and Oxen; Other poultry includes Turkeys, Ducks, and Doves.

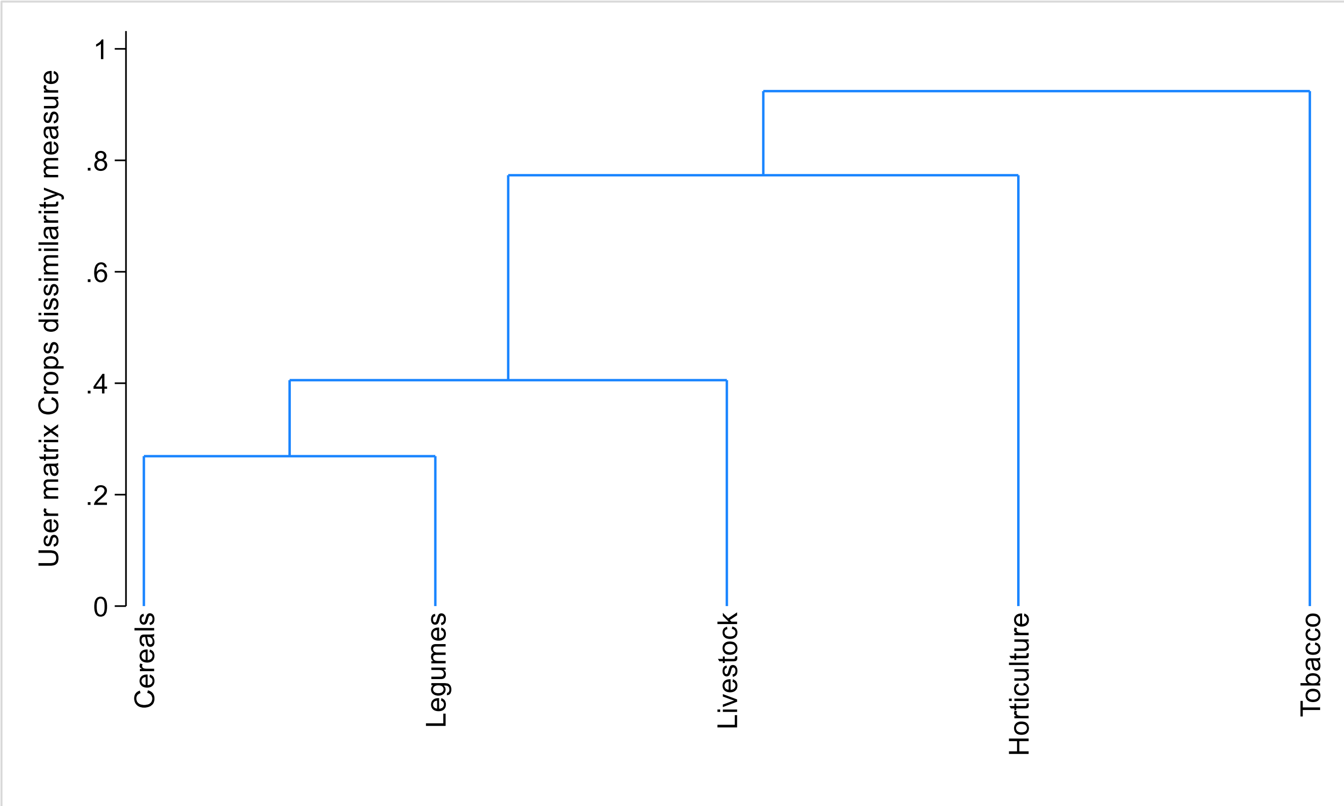
Table A4: Factors Affecting Household Participation in Agricultural Diversification Clusters, 2019 & 2024 Based on the Correlated Random Effects Probit Model Estimation

Explanatory variable	Average marginal effects	Std. error
Household head age	-0.074**	0.035
Household head is male (1=yes)	0.013**	0.006
Age of household head squared	0.000*	0.000
Household size	-0.004	0.004
Household head highest level of education		
Primary school	0.043*	0.024
Junior certificate	0.046	0.038
Secondary certificate	0.039	0.053
College Certificate	0.110*	0.061
Diploma	0.098	0.082
Degree	0.048	0.146
Durable asset index	0.031*	0.017
Agricultural asset index	0.021	0.017
Land owned (acres)	0.025***	0.009
Land owned (acres) squared	0.000***	0.000
Access to extension (1=yes)	0.048***	0.019
Access to credit (1=yes)	0.066***	0.024
Distance to livestock market	0.001	0.001
Distance to crop market	-0.001	0.002
Distance to ADMARC	0.000	0.001
Distance to the boma	-0.001	0.001
Distance to tarmac road	0.000	0.001
Household head age average	0.093**	0.04
Household head is male average	-0.005	0.006
Age of household head squared average	0.000	0.000
Household head education level average	-0.022	0.021
Durable asset index average	-0.011	0.019
Agricultural asset index average	-0.007	0.025
Land owned (acres) average	0.010	0.010
Land owned (acres) squared average	0.000	0.000
Access to extension services average	0.065**	0.028

Access to credit average	-0.052	0.034
Distance to livestock market average	-0.001	0.001
Distance to crop market average	0.002	0.002
Distance to ADMARC average	0.001	0.002
Distance to the boma average	0.001	0.001
Distance to tarmac road average	0.002	0.001
2024 survey year	-0.054***	0.017
Observations	2,352	

Source: Authors' analysis.

Figure. A1 Dendogram of Average Cluster Analysis for Crops and Livestock



Source: Authors' analysis