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Data to Decisions: Leveraging Penalized Maximum Likelihood Estimation in Agriculture

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Abstract Modelling agricultural participation is crucial for a comprehensive understanding of the agricultural sector, particularly in least developed economies where a large proportion of households rely on smallholder farming for their livelihood. Due to its importance, many households participate in agriculture in various ways along the stages of the value chain, and success often relies on several determinants. Climate change, rising input costs, alternative livelihoods, and changes in labour availability rank among the common predictors. This study utilises data from the household budget survey to explore these dynamics through Penalized Maximum Likelihood Estimation. We approach agricultural participation by examining various dimensions of agricultural output, which include output sold and household consumption, as well as production for processing and livestock feed consumption. Additionally, we consider factors such as land acquisition and farm asset ownership to provide a more nuanced understanding of participation. Our findings highlight the heterogeneity of agricultural participation, which is shaped by geographic location, household size, and income level. Importantly, the influence of these variables on participation evolves over time and differs across various forms of engagement, underscoring the need for tailored interventions to foster agricultural involvement. This holistic perspective reveals not only the multifaceted nature of agricultural participation but also the potential for diverse strategies to enhance engagement in the sector.

Keywords Agricultural Participation and Ouput; Penalized Maximum Likelihood Estimation; Logistic Regression; Imbalanced Data; Quasi-Complete Separation

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1. Introduction

Agriculture remains a generational practice in Lesotho and has served as a common source of livelihood for many households. The importance of this generational practice is evidenced by the early structuring of the agricultural programmes that occurred in the 1940s (during the period of colonial administration); see [8]. Despite its importance, subsequent years have been characterised by declining productivity, thereby threatening food security and increasing vulnerability among households. Literature attributes this decline to several factors that include: increasing migration and urbanisation, and the prevalence of HIV/AIDS [36]. In recent years, concerns have been raised about the implications of COVID-19 on agricultural practice and food security in Sub-Saharan Africa [28]; Lesotho is not immune.

These factors, while they vary by magnitude, have contributed to the reduction of the younger male population (*see* [24] – on AIDS-related deaths on young population between 1989 to 2003). This segment of the population possesses the potential to engage in heavy physical work, required to manage the conventional methods of tillage. The use of conventional methods of tillage has commonly dominated due to their accessibility to several households and their economic comparability, however, this approach often leads to low yields of subsistence farming, thus,

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failing to combat poverty. Literature recites other factors that have steadily reduced the potential agricultural output, and the examples include: the mountainous terrain that defines the country, further characterised by extensive land degradation (see Figure 1: [36]). Land of this nature is commonly argued to be unfavourable for agriculture as it is often characterised by extensively low-input and low-output farming. Furthermore, the adverse effects of unfavourable weather or climate variability acutely contribute to crop failure, thereby increasing the severity of food insecurity [6] and [39]

Figure 1. Soil Erosion in Lesotho – [36]

While climatic variability still poses a threat to crop yield, dry land farming in Lesotho offers potential, although with some uncertainty. For example, the Lesotho Bureau of Statistics identified five main crops that were planted in 2019–20 (Maize, Wheat, Sorghum, Beans, and Peas); however, most of these posited a decline in yield compared to the previous planting season, which ultimately led to an increase in the area that is fallow. These findings could suggest highly variable agricultural productivity, which leads some to claim that it has steadily declined in the last 30 years. However, agriculture remains a source of livelihood for the vast majority of the population, most of whom are engaged in subsistence farming.

1.1. Recent Developments in the Agricultural Sector

Recent years have seen the participation of the private sector in assisting subsistence farmers with scaling. The participation of the private sector – among others – was meant to encourage the adoption of climate-smart agriculture and the diversification into high-value export products [36]. Despite private sector involvement, progress has been slow due to poor profit prospects and ineffective agricultural development policies. Several factors explain this phenomenon. For example, the abandonment of fields by migrant workers and the ensuing lack of investment have restricted the adoption of goods and technologies suitable for local conditions, ultimately stifling productivity growth. At the same time, it is argued that the use of conventional tillage methods and intensive agricultural practices has contributed to increased land degradation and lower soil fertility. In contrast, progress can be seen in livestock farming (notable in Lesotho and the rest of Southern Africa), which provides a significant proportion of rural income [14]. In Lesotho, livestock is well integrated into the national and regional economy through the export of wool and mohair. The existence of the Wool and Mohair Promotion Project in Lesotho provides evidence of the efforts meant to recognise the importance of livestock farming. However, these advances are likely to be threatened by persistent droughts, poor animal quality, and insufficient disease control.

The potential that participation in the agricultural sector has, irrespective of the type of farming and its contribution to the economy of Lesotho, remains contested. This is largely explained by contradictory figures on agricultural production (in the past ploughing seasons); estimates vary. Based on the data available, it is difficult to deny that agricultural production is in a sharp decline. Commonly, factors that are mentioned as predictors of participation in agriculture include a lack of arable land (primarily due to land degradation) and an erratic climate. These issues are not new, even though they could worsen with time. As a result, there could be other plausible predictors that have emerged in recent years that explain participation, which this paper intends to explore.

2. Theoretical Framework and context to measurement

Numerous predictors have been identified in the literature to explain household participation in agriculture. Among these, demographic factors such as the age, gender, and educational level of the household head shape decision-making processes and resource allocation [17], [38]. Age, reflecting experience accumulated over time, influences familiarity of farmers with agricultural practices and their capacity for adaptation [29]. Gender roles also play a significant role; male-headed households tend to exhibit higher engagement in crop and livestock activities, although this pattern varies by geographical and sociocultural context [11]. Education further enhances access to modern technologies and information, which are critical for improving productivity and resilience in smallholder farming systems [34]. Building on this, [31] highlight that education and skills of farmers are key factors in explaining disparities in agricultural productivity both within and across countries, alongside traditional determinants such as land and water resource availability, access to inputs, credit, and infrastructural support. Beyond individual household characteristics, participation is also influenced by involvement in decision-making processes related to input management, autonomy over plot operations, and membership in farmer groups. Access to extension services and educational opportunities further contribute to sustained and inclusive agricultural participation [27]. The location of the household, whether in urban or rural settings and within specific ecological zones, directly affects the access to land, water, and market infrastructure [20], [5]. Environmental factors such as terrain ruggedness, soil fertility, and climate variability determine the types of crops and livestock suited to particular zones, thus influencing the levels of participation and adoption of new technologies [6], [39]. These environmental considerations are increasingly intertwined with climate change, which exacerbates land degradation, drought frequency, and unpredictability of rainfall, further restricting smallholder productivity [36]. Incorporating climate resilience into the theoretical framework emphasizes the importance of adaptive capacity, such as drought-tolerant crop varieties and water harvesting techniques, in shaping participation outcomes. Extending on these, economic status and access to resources are equally crucial in determining household involvement in agriculture. Household income, asset ownership, and expenditures on inputs like seeds, fertilizers, and livestock influence the capacity to invest in productive activities [30], [1]. Economic diversification strategie — including participation in markets, value addition, and access to credit or insurance schemes — are often driven by household financial resilience [14].

In general, participation in agriculture has been extensively examined in various dimensions, with many existing studies relying on data from cross-sectional household surveys, which limited the ability to establish causal relationships or understand dynamic changes over time. Notable also is that, prior research predominantly used probit and logit regression models to identify factors influencing participation in agricultural activities, often within broader regional or national contexts without focusing specifically on Lesotho. This study advances the existing literature by providing a context-specific in-depth analysis of agricultural participation of households in Lesotho, a country characterised by unique constraints such as land scarcity and increased vulnerability to climate shocks. Unlike previous studies that used primarily traditional statistical methods, this research introduces the application of penalized maximum likelihood estimation (PMLE), a robust to handling high-dimensional data, multicollinearity, and overfitting issues common in smallholder datasets. This methodological innovation allows for a more precise identification of the key demographic, environmental and economic factors influencing participation, offering nuanced insights that previous approaches may have overlooked. The originality lies in combining advanced statistical techniques with a deep contextual understanding of agricultural landscape of Lesotho, thereby offering fresh insights into how smallholder farmers can be supported to improve resilience, productivity, and livelihoods in resource-limited and climate-vulnerable settings.

3. Methods

This section provides an outline of the study area. The section also describes the context of the data collection, the variables under consideration, and the statistical consideration, which can be viewed in detail in the results section.

3.1. Study Area and Context to the data collection

Data for this study were sourced from the Household Budget Surveys, HBS. To date, three rounds of HBS have been conducted, all of which were administered by the Lesotho Bureau of Statistics (BOS) in the following years: 2002/03, 2010/11, and 2017/18. These surveys were cross-sectional in nature, having sourced the data through household interviews from the 10 administrative districts of Lesotho, which also accounts for both urban and rural strata. The HBS was designed to provide detailed information on household income and expenditure to facilitate poverty analysis, including information on social and economic indicators. The survey also examined the participation of households in economic activities, agriculture, and asset ownership, among others. The BOS applied the stratified random sampling procedure to carry out these surveys. The stratification was used to account for heterogeneity between spatial demarcations and homogeneity within the stratum. In the first stage of sampling, the Enumeration Areas were selected from the Master Frame of the historical Censuses: 1996, 2006 and 2016. The sample sizes were variable, and the distribution of the household heads was as follows: 5,992 in 2002/03; 5,318 in 2010/11; and 4,295 in 2017/18. Figure 2 shows the 10 districts of Lesotho where the three rounds of HBS were administered.

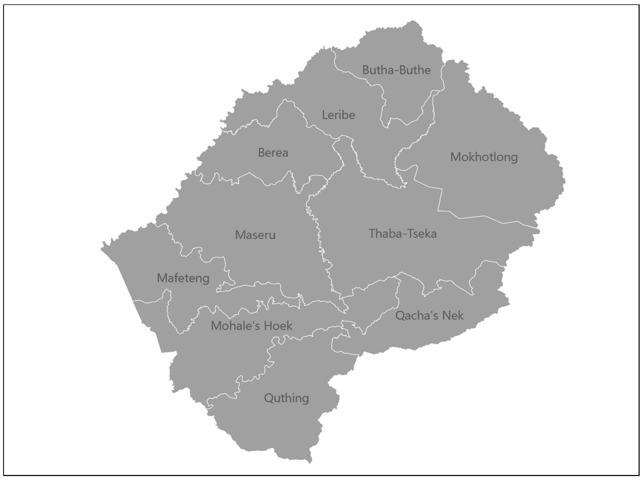

Figure 2. Districts of Lesotho – Three HBS study coverage

3.2. Description of variables

The study hypothesised that household participation in agricultural activities is a consequence of household activities that combine producer and consumption behaviour in household agroecology – including other factors such as institutional and access-related variables (i.e., utilities). The study assessed household participation in agricultural activities with perspectives from the agricultural output.

(i) Response Variables – Binary

For both livestock and crops are the main product categories of agricultural output, the study confined agricultural output to the following: output sold; output for own final consumption and output produced for further processing by agricultural producers. The definition is consistent with how the agricultural output is classified by the Organisation for Economic Co-operation and Development, OECD. Three **response or outcome variables** were proposed and measured at the agricultural output as follows:

Y_1 = household sold at least one agriculture product (binary)
Y_2 = household spending on any one agriculture product (binary)
Y_3 = household possessing in any one agriculture item (binary)

(ii) Predictor Variables – Mixed

Seventeen **predictor variables** are proposed for this study as follows:

Demographic variables

X_1 = sex of the household head (binary)
X_2 = age of the household head (continuous)
X_3 = education level of the household head (polytomous)
X_4 = household size (continuous)
X_5 = marital status of the household head (polytomous)

Geographic setting

X_6 = urban/rural setting where household is located (binary)
X_7 = district where household is located (polytomous)
X_8 = ecological zone where household is located (polytomous)

Economic variables

X_9 = household income in quintiles (polytomous)
X_{10} = economic Activity of the household head (polytomous)
X_{11} = household spending on new farming house or repairs (binary)
X_{12} = household spending on irrigation (binary)
X_{13} = household spending on land conservation and improvements (binary)
X_{14} = household spending on animal drawn vehicles (binary)
X_{15} = household spending on cattle (binary)

Utilities

X_{16} = access to water by the household (binary)
X_{17} = access to electricity by the household (binary)

3.3. Support for the choice of variables

Demographic Variables

Household characteristics (age of the household head, education, household size, and gender of the household head) are important factors in determining the participation of the household in agricultural activities. For instance, the age of the household head – considered the decision making body of the household – is incorporated because it is believed that, with age, the connection to farming as a generational practice occurs. A complementing observation by [29] is that, the age of the farmer is associated with experience, thus, increasing the likelihood of participation in agricultural activities. In contrast, it can be argued that younger household heads are more flexible, eager for new information, could explore new technology, could have studied modern agricultural practices – therefore, highly likely to participate. The contrasting views posit potential differences that can be statistically tested for homogeneity on practices between old age household heads and the younger population. The sex of the household head is included in the model to capture the differences in sex, some of which can be explained by the social environment. For instance, a study by [11] reflected lower participation rates for female farmers, who comprise 50 percent of the agricultural labour force in the Eastern and Sub-Saharan region. The finding could indicate a potential for higher food insecurity in female-headed households, and the contrasting pattern could be argued for male-headed households. For instance – [26] and [35] – observed higher participation in male headed households, most of which participated in extension activities and the adoption process than their female counterparts, however, the geographic setting plays a major role in explaining these differences as no statistical differences were observed by [22].

In addition, the study observes the likely potential that the education level of the household head could bring in explaining participation in agricultural activities, including productivity (see [34]). Educated household members or farmers are typically assumed to be better placed to process information (could be appropriate technologies to address production constraints, weather and its effects on farming and so on). A person who is educated, suggesting attainment of some level of literacy is able to follow instructions, say, for chemical inputs and other aspects of agricultural technology [4]. The household size has also been considered in the model specification of this study. The consideration draw basis from the fact that a household represents a unit of people in which resources are pooled, income is shared, and participation in activities including agriculture is likely to vary based on the household structure. Often, households are associated with farming activities, sometimes as alternative sources of livelihood. Extending on this, [2] ascertains this by making an observation of the relationship between household size and participation in agriculture – reflecting increases in vulnerability for increasing household size. It is therefore expected that, on the assumption of *ceteris paribus*, the larger the household size, the greater the probability of participation in agricultural activities.

Geographic Setting

The geographic setting – such as the district, ecological zones and urban-rural setting of the household has a potential to catalyse participation in agriculture, and this is in line with the literature which attributes participation in agriculture to geographic features such as access to water, climate, soil types and landforms. These features are referred to as demographic pressures due to their bearing on agricultural participation and productivity. These pressures can also extend to include: the lack of infrastructure, transportation facilities, and other social amenities, the search for fertile soil and land space coupled with the need for risk minimization through crop and land diversification [20]. This is further corroborated by [5] who reflect on the negative impact of farming on land utilization. In the case of Lesotho, which is characterised by difficult terrain and erratic weather conditions, the argument for the effect of the geographic setting on agricultural production seems plausible and can be hypothesised to predict household participation.

Economic Variables

Certain aspects of the economic activity of the household have the potential to affect the participation of households in agriculture, and as such have been identified for inclusion in the study. Agriculture as an activity, is among the main sources of income for households and farmers alike, however, to realise its potential – including the transitioning towards commercialization, some considerations such as resources for scaling are a requirement. To corroborate this theoretical consideration, literature asserts agricultural growth on technical change, and adoption of new technology, and these are dependent on the availability of funds and terms of financing among others [30]. The ability of the household to finance these activities including spending on the right resources is important. This study makes a hypothesis that the economic activities of the household, household income and household expenditure on agriculture-related resources such as the farming house, irrigation system and livestock could explain the participation of the household in agricultural activities.

Access to Utilities – electricity and water

Access to electricity and water are important input factors for agricultural activities, both having a bearing on agricultural output (i.e., adoption of electrical equipment by agricultural producers, and supply and manning irrigation systems). For instance, the nexus between access to electricity by the household and the participation of the household in agricultural activities presents a potential to use powered equipment at all phases of the production cycle and also for irrigation [10]. Similarly, for access to water for livelihood and domestic activities (such as irrigation), studies posit the potential towards improving various determinants of under-nutrition and income generation – see [9]. On this basis, the study makes a hypothesis that even in the context of Lesotho, access to electricity and water presents a potential to influence the participation of households in agricultural activities.

3.4. Caveats regarding the consistency of variables and implications on measurement

Although this study provides valuable information on household participation in agriculture in Lesotho, several limitations should be recognised. First, the distribution of participation is heavily skewed, with a relatively small proportion of households actively engaged in agricultural activities versus those not participating at all. This skewness can pose challenges for statistical separation and can lead to issues such as separation in regression models, potentially affecting the stability and interpretability of the estimated predictors. Second, the HBS data utilised are cross-sectional in nature, which limits the ability to directly infer causality or capture dynamic changes within households over time. However, due to the consistent application of large sample sizes aligned with the law of large numbers, as well as the general similarity in survey design and data collection methods across survey rounds, the observations are comparable over the years. This consistency provides some assurance that trends and patterns can be analysed with a level of reliability, despite the absence of true longitudinal tracking at the household level. Third, although the HBS design has generally been maintained over the three survey periods, certain modifications in the questionnaire were introduced in subsequent rounds. These changes, while possibly responding to emerging issues or observations, complicate the direct comparison of parameters over time. For example, differences in how the questions are phrased, such as the question on land ownership (”possession of land in hectares” in HBS 2002/03 versus ”assessing whether the household cultivates or owns any land in the last completed farming season” in HBS 2017/18) may influence the interpretations and responses of the respondents [19]. Similarly, alterations in the measurement of expenditures, for instance, reporting irrigation works costs in HBS 2002/03 versus expenditures on watering cans in HBS 2010/11, further hinder direct comparability. These variations can introduce measurement inconsistencies that affect the analysis of temporal trends. In general, while the large sample size and consistent survey approach lend some robustness to temporal comparisons, these limitations highlight the need for cautious interpretation of longitudinal inferences and underscore challenges in tracking changes in household agricultural participation over time.

3.5. Analytical Framework

The Penalized Maximum Likelihood (PLM) Estimation or the FIRTH logistic regression has been used to investigate the effects of certain aspects of household activities related to agriculture, further assessing their relationship in predicting participation in agriculture. FIRTH regression was first introduced by David Firth [12], and is considered a promising method for dealing with separation. The procedure is further considered promising in addressing issues that can arise from the use of standard maximum likelihood estimation, and these are common for small data sets, imbalanced data sets and separated data sets. As a context, our study model specification builds on the premise that participation of the household in agriculture, at the output level, is a function of certain household demographic variables, economic variables and the acquisition of certain variables that could contribute to implementing agricultural activities. These variables are drawn from three HBS data sets that reflect the characteristic of an imbalance. From the standard classification of some of the variables in the data sets, the classes vary greatly reflecting the potential bias or skewness (i.e., household expenditure on agriculture-related items, access to land, access to water, etc.). This type of data structure has the potential to suffer from an imbalanced classification problem out of which the application of standard testing methods could skew coefficients and standard errors. For instance, the use of the standard logistic regression models is associated with the failure of the likelihood maximisation algorithm to converge, and ignoring this failure could lead to the emergence of the complete or quasi-complete separation ([3]. Commonly, quasi-complete separation occurs when the dependent variable partially separates an independent variable or a combination of several independent variables. In other words, groups in a discrete outcome variable separate levels in a categorical variable or values in a numeric variable. There are many computational implications that are brought by separation, and the PLM becomes a remedy for dealing with such [33] and [18]. The PLM is further considered easier to implement and less computationally intensive compared to alternative approaches (i.e., permutation or bootstrapping); see [37]

The Model:

Through the PLM, the idea is to introduce a more effective score function by including a term that counteracts the first-order term from the asymptotic expansion of the bias of maximum likelihood estimation; infusing this term, especially for a small sample will decrease to zero as sample size increases [12] and [16]). An important highlight of the PLM is that it provides bias-reduction for small sample sizes and generates finite and consistent estimates where separation is inevitable [37]. The breakdown of the FIRTH model is outlined in the equations that follow. The method is deduced from the work of Newton-Raphson Algorithm who calculated the vector of first derivatives as follows:

$$\cup(\beta) = \frac{\partial LogL}{\partial \beta} = \sum_i x_i y_i - \sum_i x_i \hat{y}_i - \sum_i h_i y_i (0.5 - \hat{y}_i), \tag{1}$$

where, h_i is the i^{th} diagonal element of the "hat" matrix H

$$H = W^{1/2} X (X^{'} W X)^{-1} X^{'} W^{1/2} \tag{2}$$

and

$$W = diag\{\hat{y}_i(1-\hat{y}_i)\} \tag{3}$$

The order of implementation of the approach is further corroborated by [25], who postulate that the correction is the shrinkage quantity that is intended to remove the bias, and it does this by adding one-half of the natural logarithm of the information matrix to the log-likelihood while it simultaneously adjusts the Score function. The duo further indicate that, as the log-likelihood declines to zero over iterations, the adjustment serves to counteract the bias. To study the effect of the model parameters on participation in agricultural activities, the study will interpret the Odds Ratios, OR, and the Confidence Intervals (CI) of the Odds Ratios. We recall from the literature that the regression coefficient in the population model is the log(OR), thus, the OR is obtained by exponentiating β as follows; see [15]:

$$e^{\beta} = e^{log(OR)} \tag{4}$$

and to determine the 95% Confidence Interval of the Odds Ratios, the following expression is used:

$$\left(e^{ln(\hat{\beta}) - z_{\alpha/2} * s^*}, e^{ln(\hat{\beta}) + z_{\alpha/2} * s^*}\right) \tag{5}$$

where, z is the level of confidence represented, *i.e.*, 95% and s is the standard error.

3.6. Model Specification

The results discussed in this study are based on the PLM model specifications. The model specification refers to the determination of which independent variables be included or excluded from a regression formula.

3.6.1. Outcome Variable (s) — binary in nature

The study modelled the relationship between household participation in agriculture activities, assessed on Agricultural Output. The model specification has considered agricultural output sold and agricultural output consumed as the binary outcomes of the study model.

3.6.2. Explanatory Variables

The study identified seventeen variables to explain agricultural the variations in agricultural output in the household, and the choice of their support is provided in section 3.3. These variables comprise of a number of demographic, socio-economic and environmental factors such as sex of the household head, age of the household head, education attainment of the household head, employment status of the household head, household size, household income, and access to land.

4. Results

This section provides summary statistics of the variables.

4.1. Descriptive Statistics – Response Variables

Table 1 shows the distribution of households and their participation in agricultural activities through selling any one agricultural product over the past month of each survey administration period. Over the three HBS rounds, participation by households was marginal, declining from proportions at 13.4% in 2002/03 to 3.6% in 2017/18. The same was true for participation by setting (i.e., urban/rural strata). Further notable from the table is that this decline in participation in recent years was statistically significant, with p-value = 0.000 ¡ 0.05 irrespective of categorisation by period.

Table 1. Proportions (%) in Household Participation: assessing whether the household sold any Agric Product by HBS round

	HBS Year			
Total	2002/03	2010/11	2017/18	χ^2 (p-value)
No participation	86.6%	93.4%	96.3%	341.9 (0.000)
Participate	13.4%	6.6%	3.7%	
Urban				
No participation	90.8%	91.1%	96.2%	77.5 (0.000)
Participate	9.2%	8.9%	3.8%	
Rural				
No participation	82.1%	96.3%	96.5%	383.1 (0.000)
Participate	17.9%	3.7%	3.5%	

The study further assessed the participation of households in agricultural activities measured against their expenditure on any one agricultural product over the last month, for each HBS round. Table 2 presents the results. As illustrated in the table, spending by households on agricultural products was relatively low across the three HBS rounds, reflecting a cyclical pattern between 2002/03 and 2017/18. The pattern is also true for urban and rural setting, and in general, the differences in spending were statistically significant (see p-value = 0.000 ¡ 0.05 irrespective of categorisation).

Regarding other aspects of agricultural output, Table 3 details the distribution of households and their participation in agricultural activities, as indicated by their possession of at least one agricultural item in the month preceding each survey administration. For context, the criteria for possession was based on the premise of a household owning any one of the agricultural-related items commonly owned by farming households or

Table 2. Proportions (%) in Household Participation: assessing whether the household spend on any one Agric Activity by HBS round

	HBS Year			
Total	2002/03	2010/11	2017/18	χ^2 (p-value)
No participation	91.8%	96.7%	82.7%	575.5 (0.000)
Participate	8.2%	3.3%	17.3%	
Urban				
No participation	91.7%	95.5%	84.0%	230.4 (0.000)
Participate	8.3%	4.4%	16.0%	
Rural				
No participation	91.9%	98.1%	80.3%	378.4 (0.000)
Participate	8.1%	1.9%	19.7%	

smallholder farming as an activity. These included: the availability of land, the availability of cattle and the availability of ploughing implements. It can be deduced from the table that possession of agricultural items across households was relatively common, with almost three third of the households owning either one item in 2002/03 and 2017/18, contrasting with observations made in 2010/11. The pattern is also true for urban and rural setting, and in general, the differences in possession were statistically significant.

Table 3. Proportions (%) in Household Participation: assessing whether the household possessed any one Agric item by HBS round

	HBS Year			
Total	2002/03	2010/11	2017/18	χ^2 (p-value)
No participation	32.4%	67.4%	31.0%	1805.1 (0.000)
Participate	67.6%	32.6%	69.0%	
Urban				
No participation	49.9%	53.1%	18.9%	841.6 (0.000)
Participate	50.1%	46.9%	81.1%	
Rural				
No participation	14.2%	84.5%	54.1%	2656.7 (0.000)
Participate	85.8%	15.5%	45.9%	

However, despite this relatively consistent level of agricultural asset ownership, Figure 3 reveals a contrasting trend when examining active participation in agriculture through market engagement across geographic setting. Specifically, there was a significant decrease in household participation in agriculture through the sale of agricultural products in all districts between the 2002/03 and 2017/18 periods. While some districts saw temporary increases, the overall trend points to a marked decrease in market-oriented agricultural activity at the household level, suggesting that even with the means of production (as indicated by asset ownership), households are increasingly less likely to be selling their produce. This widespread decline highlights potential challenges impacting the ability of smallholder farmers or incentive to produce for the market, which could include factors like climate change [23], market access issues, or shifts in household livelihood strategies, despite their continued ownership of agricultural assets. Adding another dimension to household engagement with agriculture, the data on household participation by spending on agricultural items presents a different picture. After a general decline between 2002/03 and 2010/11 in most districts, there was a substantial increase in the percentage of households reporting spending on agricultural items in 2017/18. Districts that include Butha-Buthe, Leribe, Maseru, and Mafeteng, among others, show significantly higher participation in this category in 2017/18 compared to the earlier periods. This suggests that while fewer households may be selling agricultural products, a growing proportion are investing in inputs or resources for agricultural activities, potentially indicating a shift in the nature of agricultural engagement or a focus on subsistence farming rather than market production. The rise in spending on agricultural items alongside the decline in selling agricultural products warrants further investigation to understand the evolving dynamics of household involvement in agriculture. Further analysis of household participation in agriculture, specifically focusing on the possession of agricultural items or products, reveals a trend that aligns more closely with the initial observation regarding asset ownership. The data shows that, after a decline in most districts between 2002/03 and 2010/11, the percentage of households possessing agricultural items or products rebounded significantly by 2017/18. In fact, in many districts, the participation rate in 2017/18 surpassed the levels observed in 2002/03. Districts such as Butha-Buthe, Mafeteng, Mohale's Hoek, Quthing, Qacha's Nek, Mokhotlong, and Thaba-Tseka all demonstrate a strong resurgence in the proportion of households owning agricultural assets or products. This finding reinforces the idea that households generally retain the means of agricultural production.

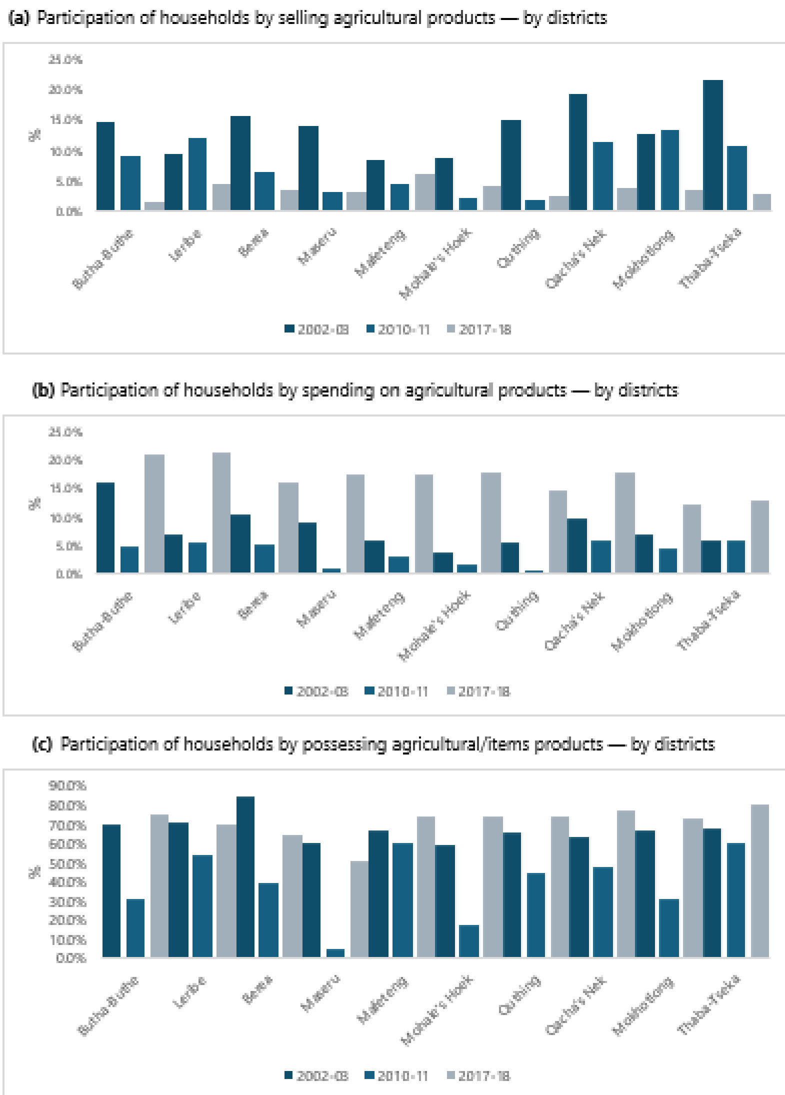

Figure 3. Agricultural participation of households across districts – assessed on selling Agric products, spending on Agric activities and possession of Agric items/products

When considered alongside the decreased market participation (selling products) and increased spending on agricultural items, this suggests a complex picture where households are maintaining their connection to agriculture through ownership and investment, even if market-oriented production is declining. This could imply a greater emphasis on subsistence farming or a reallocation of resources within the agricultural sector at the household level. Analysis of agricultural participation by ecological zone reveals different patterns influenced by varied weather and terrain (Figure 4). In particular, the data on participation by selling agricultural products demonstrates a significant decline across all ecological zones between 2002/03 and 2017/18. The Mountains zone consistently showed the highest participation in selling in 2002/03 and 2010/11, potentially reflecting a greater reliance on agriculture for income in these more remote areas. However, this zone also experienced the most drastic drop in selling participation by 2017/18, reaching the lowest level among all zones. This could be attributed to the harsher weather conditions and more challenging terrain in the mountains, making agricultural production more vulnerable to climate variability and market access more difficult. The Lowlands, Foothills, and Senqu River Valley also saw substantial decreases in selling, suggesting a widespread challenge to market-oriented agriculture across the country, regardless of ecological characteristics. In contrast to the declining trend in selling, participation by spending on agricultural items shows a significant increase across all ecological zones between 2010/11 and 2017/18, after an initial decline from 2002/03. The Lowlands and Foothills zones exhibit the highest rates of spending on agricultural items in 2017/18, potentially reflecting greater access to agricultural inputs and markets in these more accessible areas. While the Mountains and Senqu River Valley also show increased spending, their rates remain lower, possibly due to the logistical challenges of transporting inputs to these areas. This rise in spending, despite the decrease in selling, suggests that households are continuing to invest in agriculture, perhaps shifting towards subsistence farming or adapting their practices to the changing environmental conditions. Lastly, examining participation by possession of agricultural items or products reveals a complex pattern influenced by ecological factors. While there was a general decline in possession between 2002/03 and 2010/11 across all zones, the recovery by 2017/18 was more pronounced in the Foothills, Mountains, and Senqu River Valley compared to the Lowlands. The Foothills zone shows the highest possession rate in 2017/18, nearly returning to its level in 2002/03, which could be attributed to a combination of relatively favourable terrain and access to resources.

The Mountains and Senqu River Valley also demonstrate a strong rebound in possession, suggesting that despite the challenges of selling, households in these areas are maintaining their agricultural assets. The lower recovery rate in the Lowlands might indicate a greater diversification of livelihoods away from traditional agriculture in this more urbanized zone. In general, the ecological zones of Lesotho present distinct challenges and opportunities for agricultural participation, with the Mountains potentially facing particular difficulties in market engagement due to weather and terrain, while all zones show a shift towards increased investment in agricultural inputs despite declining sales.

4.2. Regression Results – Effect of predictors

The results presented here are derived from a Firth penalized likelihood model (FR). While Firth regression is employed to address potential separation issues, a comparison with standard logistic regression (LR) was conducted to confirm the robustness of the findings. The results reflect the effects of the identified choice of demographic variables, geographic setting, economic variables, and access to utilities in predicting the participation of households in agricultural activities. Table 4 shows the regression outputs for the HBS data sets where the response variable is possession of any one agricultural product. The study hypothesised the reference category as *no participation* in agricultural activities by the households. The results from the models suggest that, in 2002/03, the geographic location (urban/rural, p-value = 0.000; ecological zone, p-value = 0.018; and district, p-value = 0.000) of the household, household size (p-value = 0.000), sex of the household head (p-value = 0.000), age of the household head (p-value = 0.000), marital status of the household head (p-value = 0.000), household income (p-value = 0.000) and access to water (p-value = 0.002) were significant factors influencing the participation through ownership of at least one agricultural item. Comparing the FR results with the LR for 2002/03, we observe very close agreement in both the estimated coefficients (Odds Ratios) and the statistical significance (p-values) for all significant variables. For instance, the urban/rural AOR is 0.2800 in Firth and 0.2834 in Logistic, both with p-values of 0.0000. Similarly, the ecological zone AOR is 1.1400 (Firth) and 1.1453 (Logistic), with p-values of 0.0180 and 0.0172 respectively. This suggests that for the 2002/03 data, separation was likely not a significant issue, and both models yielded highly comparable results. Further notable from the results is that the urban-rural setting (with its categorisation) has an AOR of 0.28 and 95% CI at 0.22–0.37. The AOR indicates that, for households living in

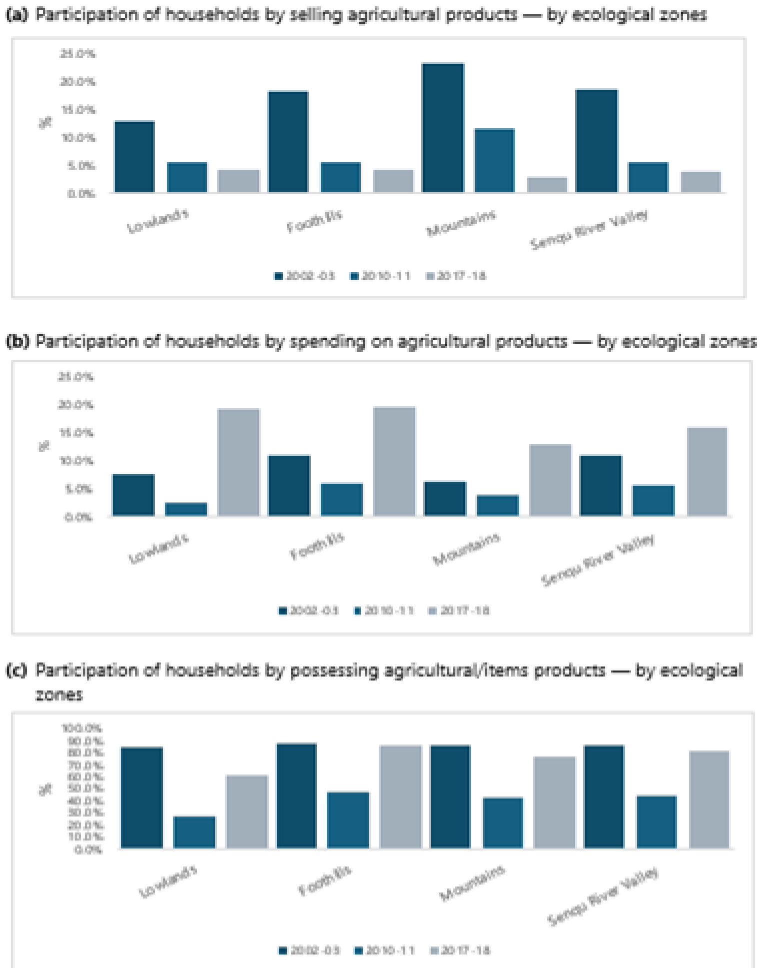

Figure 4. Agricultural participation of households across ecological zones – assessed on selling Agric products, spending on Agric activities and possession of Agric items/products

rural areas and not participating in agricultural activities, their odds of not participating are relatively low compared to families living in urban centres if also assessed on non-participation. The observation can be attributed to the availability of agricultural land in rural areas which can be accessed for producing agricultural products and rearing livestock, thus promoting participation. The opposite is true for urban centres and the extension of this observation can further be attributed to conflicts between rural and urban interests. The observation could further indicate the restrictions that may come with the location in influencing the possession of certain items such as the acquisition of land for farming (which is mainly residential in the urban areas and characterised by small plots). More can be mentioned on how the setting could influence ownership of livestock (i.e., cattle) and other ploughing implements, most of which may remain dormant due to lack of use, especially in the urban centers. The ecological zone also reflects a statistically significant effect in predicting the participation (or not) by households with an AOR of 1.14 and 95% CI at 1.02–1.28. The AOR could reflect the influence that ecological zone has on landform and climatic characteristics (i.e., the cold weather in the mountains which not be favourable for crop farming, which contrasts with the weather conditions experienced in the lowlands which are also variable and event-based – dry, windy, floods). The study further observed the significant effect of household size in predicting household participation in agricultural activities.

Table 4. Adjusted Odds Ratios (AOR) generated for households possessing any one agricultural item – comparing Logistic Regression (LR) and Firth Regression (RF)

	Dependent variable: Possess any one Agric item					
	2002/03		2010/11		2017/18	
Variable	LR[AOR, Sig.]	FR[AOR,Sig.]	LR[AOR, Sig.]	FR[AOR,Sig.]	LR[AOR, Sig.]	FR[AOR,Sig.]
urban/rural	[0.28, 0.000]	[0.28, 0.000]	[5.45, 0.000]	[5.40, 0.000]	[2.25, 0.000]	[2.25, 0.000]
zone	[1.15, 0.017]	[1.14, 0.018]	[0.79, 0.001]	[0.79, 0.000]	[1.11, 0.054]	[1.11, 0.053]
district	[0.94, 0.000]	[0.94, 0.000]	[1.05, 0.064]	[1.05, 0.064]	[0.96, 0.074]	[0.96, 0.074]
household size	[1.19, 0.002]	[1.19, 0.000]	[1.29, 0.000]	[1.28, 0.000]	[1.23, 0.000]	[1.23, 0.000]
sex	[0.53, 0.000]	[0.53, 0.000]	[0.67, 0.002]	[0.67, 0.002]	[0.61, 0.000]	[0.61, 0.000]
age	[1.03, 0.000]	[1.03, 0.000]	[1.02, 0.000]	[1.02, 0.000]	[1.04, 0.000]	[1.04, 0.000]
marital status	[1.21, 0.000]	[1.21, 0.000]	[1.04, 0.139]	[1.04, 0.140]	[1.02, 0.415]	[1.02, 0.416]
education level	[0.96, 0.144]	[0.96, 0.146]	[1.03, 0.476]	[1.03, 0.479]	[0.94, 0.024]	[0.94, 0.025]
economic activity	[0.98, 0.091]	[0.84, 0.090]	[0.92, 0.507]	[0.92, 0.509]	[0.94, 0.465]	[0.94, 0.464]
access to electricity	[0.97, 0.732]	[0.97, 0.729]	[0.86, 0.192]	[0.86, 0.191]	[1.03, 0.747]	[1.03, 0.743]
household income	[1.00, 0.000]	[1.00, 0.000]	[1.00, 0.030]	[1.00, 0.029]	[1.00, 0.475]	[1.00, 0.520]
spend on house for farming	[1.21, 0.863]	[0.87, 0.883]	[——, —]	[——, —]	[7.58E8, 1.000]	[1.41, 0.828]
spend on land conservation	[0.90, 0.915]	[0.83, 0.842]	[——, —]	[——, —]	[——, —]	[——, —]
animal drawn vehicles	[4.94E8, 0.999]	[2.47, 0.530]	[——, —]	[——, —]	[——, —]	[——, —]
spend on scotch cart	[1.26E8, 0.999]	[0.59, 0.744]	[——, —]	[——, —]	[——, —]	[——, —]
spend on cattle	[4.32, 0.158]	[2.96, 0.143]	[——, —]	[——, —]	[——, —]	[——, —]
access to water	[1.35, 0.002]	[1.35, 0.002]	[1.25, 0.245]	[1.24, 0.250]	[1.85, 0.000]	[1.85, 0.000]
intercept	[1.91, 0.137]	[1.92, 0.136]	[0.02, 0.000]	[0.02, 0.000]	[0.03, 0.000]	[0.03, 0.000]

Variables: Urban/Rural, Household size Category, Sex, Age, Marital Status, Supplied Electricity, Economic Activity, Education level, Paid for Land conservation and improvements, Purchased Animal Drawn vehicles, Paid on Cattle, Access to own Water (within premises).

The AOR of household size is 1.19 and it is included in the 95% CI of the observations, ranging between 1.15 and 1.22. The AOR is interpreted to reflect that a unit increase by a household member within a family setting is likely to influence non-participation by $\approx 20\%$ and this could suggest that the odds are potentially higher on household participation for any unit addition to the family composition or structure. A slight contrast is observed in 2010/11 where, within the geographic setting, the district could not reflect statistical significance. Examining the 2010/11 results from the two models, the district variable shows a p-value of 0.0638 in the Logistic Regression and 0.0640 in the Firth Regression. Neither model indicates statistical significance at a conventional 0.05 level, and the estimated AORs are very close (1.0495 for Logistic and 1.0500 for Firth). Other parameters such as the household size (p-value = 0.000), the sex of the household head (p-value = 0.002), the age of the household head (p-value = 0.000), and the household income (p-value = 0.029) were significant predictors of participation in agriculture through ownership of either one related item. Again, for these significant variables in 2010/11, the Firth and Logistic Regression models produced very similar AORs and p-values. For example, household size has an AOR of 1.2867 (Logistic) and 1.2800 (Firth), both with p-values of 0.0000. The sex of the household head has an AOR of 0.6725 (Logistic) and 0.6700 (Firth), with p-values of 0.0017 and 0.0020 respectively. This consistent agreement across significant predictors in 2010/11 suggests that, despite the observed decline in overall participation, the potential for separation impacting the estimates of these key variables was not substantial. The other significant aspect of the results is the high AOR for the urban-rural setting (AOR = 5.40) with its corresponding 95% CI of 4.33 to 6.74. While the AOR indicates that the likelihood of rural population is 5 times not likely to participate in agricultural activities versus their urban counterparts, the observation is not surprising in that, for the reference year, overall participation was 32.6% down from 67.6% registered in 2002/03. The decline was high in rural areas, with participation registering 15.5% in 2010/11 from 85.8% in 2002/03 (and this contrasts with a general plateau observation in the urban centres at 49.9% in 2002/03 to 53.1% in 2010/11). Relatedly, the sex of the household head reflected the statistical effect towards household possession of either agricultural item with an AOR at 0.64 and 95% CI range from 0.53 to 0.86. The likely interpretation of the AOR is that male-headed households were less likely not to participate in agricultural activities compared to female-headed households. This result is plausible in that, culturally in the Basotho household setting, males are assigned household headship (and often this is not defined by objective criteria but is self-identified by respondents, [32]. For women heading households (which may be true for widows or if the spouse to the woman is away), often the decision to choose to possess certain agricultural items remains limited. Access to the land remained a gendered process and this is common in the rural areas despite the enactment of the *Legal Capacity of Married Persons Act 2006* ([13]); often marriages in the rural areas are of customary nature. In 2017/18, among the geographic variables, only the urban-rural setting (p-value = 0.000) was significant. Other variables that reflected significance include household size (p-value = 0.000), sex of the household head (p-value = 0.000), age of the household head (p-value = 0.000), education level of the household head (p-value = 0.025), and access to water (p-value = 0.000). Comparing the 2017/18 results, the significant variables again show very close correspondence between the Firth and Logistic Regression models. For instance, urban/rural has an AOR of 2.2524 (Logistic) and 2.2500 (Firth), both with p-values of 0.0000. Household size has an AOR of 1.2335 (Logistic) and 1.2300 (Firth), both with p-values of 0.0000. Education level, with a p-value of 0.0242 in Logistic and 0.0250 in Firth, also shows very similar AORs (0.9370 and 0.9400). The consistency in both the magnitude and significance of the estimated effects across the significant variables in 2017/18 further indicates that the potential for separation did not lead to substantial differences between the two modeling approaches for the key predictors identified. As a context, household access to water within the premises registered an AOR of 1.85 with true values lying between the CI values of 1.49 and 2.29. While literature connects access to water to the agricultural production chain (as a plausible means of irrigation [[23]]), the AOR reflects that those with access to water are 1.9 times not to participate in agricultural activities. The observation is plausible in that, for households with access to water in their premises, most of them reside in urban centres where consumption is largely household based (i.e., cooking, etc). Even for those households who could still be using water for agriculture-related activities, their usage is likely marginal due to the cost associated with water usage.

Table 5 shows the regression results for the HBS data sets where households participated in agricultural activities by selling at least one agriculture product during the reference period of the survey. In the 2002/03 HBS, both the Firth Regression and standard Logistic Regression models identified a similar set of statistically significant variables influencing trading of households on certain agricultural commodities (considered participation at output sold). These included: the ecological zone of the household (p-value = 0.000 for both), the household size (p-value = 0.000 for Firth, p-value = 0.977 for Logistic - a notable difference in significance for household size), the age of the household head (p-value = 0.009 for both), the education level of the household head (p-value = 0.022 for Firth, p-value = 0.021 for Logistic - very similar significance levels), the household income (p-value = 0.000 for both), and the expenditure on cattle (p-value = 0.041 for Firth, p-value = 0.080 for Logistic - Firth shows stronger significance for expenditure on cattle). The ecological zone reflects a non-chance effect in predicting participation by households with an AOR of 1.22 and 95% CI at 1.10–1.36 in the Firth model (and identical AOR and very similar CI in the Logistic model), which could reflect the dynamics in the trading of agricultural products, and how they are likely influenced by the location (due to climate and landforms). For example, livestock farming drives agricultural participation in mountainous areas, whereas crop production is common in the lowlands, promoting trade between the zones. The result of household size (AOR = 1.06; 95% CI at 1.03 to 1.09 in the Firth model) is also plausible in that larger households are associated with higher demands for consumption goods, as well as a higher likelihood of poverty and vulnerability, owing primarily to the effects of HIV/AIDS. Therefore, the $\approx$ 6% chance of households not participating with the increasing household size is indicative of the distribution that is likely skewed towards participation. A plausible connection could be that the engagement of households in selling at least one agricultural product can be considered a coping mechanism or a means of generating an alternative source of livelihood, which may become dire with increases in household size. It is interesting to note the substantial difference in the p-value for household size between the two models (0.000 for Firth vs. 0.977 for Logistic), suggesting that Firth's penalized likelihood approach may be more sensitive to the effect of household size in this dataset. Participation effects have been observed to have declined in recent years. For instance, in 2010/11, three predictors were significant as follows: the urban-rural setting (AOR = 2.02; 95% CI at 1.40 to 2.92 in the Firth model, and very similar AOR and CI in the Logistic model), household size (AOR = 1.15 and 95% CI between 1.02 and 1.30 in the Firth model, and identical AOR and similar CI in the Logistic model), and district (AOR = 0.90 and 95% CI not shown, with identical AOR and p-value in the Logistic model). From a viewpoint of the urban-rural setting, access to the markets in urban centers and the related trade in agricultural produce could explain this effect. Despite the daily small-scale trade, trade continues to take place in both settings through organised forums, such as trade shows. In 2017/18, neither the Firth nor the Logistic Regression model found any of the chosen predictors to have a statistically significant effect. As an overall observation and while many of the coefficient estimates and their significance levels are consistent between the Firth and Logistic Regression models across the different survey years, there are instances where the Firth model appears to provide more robust or statistically significant results, particularly for variables like household size and expenditure on cattle in the 2002/03 data. This aligns with the expectation that Firth Regression can be beneficial in situations where separation might affect the performance of standard Logistic Regression.

Table 6 shows the regression results for the HBS data sets where the response variable is whether the household registered any form of expenditure on items or activities that reflect participation in agriculture. The results suggest that in 2002/03, the ecological zone of the household (p-value = 0.006), the district of the household (p-value = 0.000), household size (p-value = 0.000), marital status of the household head (p-value = 0.003), the education level of the household head (p-value = 0.021), the economic activity of the household head (p-value = 0.020), household income (p-value = 0.026), spending in cattle (which could be part of the value chain, p-value = 0.000), and access to water (p-value = 0.004) were significant factors influencing the participation of the household in agricultural activities by owning at least one item. Across these significant variables in 2002/03, the estimated odds ratios from the Firth Regression are largely consistent with those from the standard Logistic Regression model, and the significance levels (p-values) show minimal differences. The ecological zone with an AOR = 1.22 and further characterised by different land formations, weather patterns, precipitation intensity, and variability among the characteristics, influences the direction of spending (including agricultural activities). For instance, households residing in the lowlands are 22% likely not to spend on agricultural items, leaving a greater chance towards spending, and the odds are likely variable within and across ecological zones. The spending may also be aligned with the livelihood strategies that exist within the ecological zone; agriculture is key among the list. In addition, the district with an AOR at 0.89 and 95% at 0.86 to 0.93 could be a reflection of the diversification of household spending between districts, which may be argued to be skewed towards agricultural items in the rural parts of the districts, a clear contrast with urban areas with a likely different basket of goods. In 2010/11, urban-rural setting (p-value = 0.038), household size (p-value = 0.000), education level of the household head (p-value = 0.025), and access to water (p-value = 0.000) were significant predictors of participation. For the 2010/11 data, the Firth Regression and Logistic Regression models yield very similar results in terms of both estimated odds ratios and significance levels for the identified predictors. To provide the context, the result of household size (AOR = 1.30) is plausible given that increases in household size may imply a need for an increase in spending on the main sources of livelihood for such a household (i.e., expenditure on food, intermediate goods, and so on). Household expenditure will likely increase by some unit for increasing households, however, the age of the additional member may be a factor to consider especially for household composition with infants; this could explain the 30% unlikely participation. Increases in household size and related household activities are also influenced by the location of the household (i.e., urban-rural setting). A general observation which is also consistent with the global view is that larger families tend to be poorer and this is true for developing countries [21], and in Lesotho; agriculture provides an alternative source of income for poorer households and becomes more important for larger families. The latest HBS (2017/18) identified five statistically significant predictors as follows: urban-rural setting

Table 5. Adjusted Odds Ratios (AOR) generated for households having sold any one agricultural product – comparing Logistic Regression (LR) and Firth Regression (RF)

	Dependent variable: Sold any one Agric Product					
	2002/03		2010/11		2017/18	
Variable	LR[AOR, Sig.]	FR[AOR, Sig.]	LR[AOR, Sig.]	FR[AOR, Sig.]	LR[AOR, Sig.]	FR[AOR, Sig.]
urban/rural	[0.80, 0.124]	[0.75, 0.122]	[2.03, 0.000]	[2.02, 0.000]	[0.95, 0.819]	[0.94, 0.798]
zone	[1.22, 0.000]	[1.22, 0.000]	[1.17, 0.129]	[1.17, 0.125]	[0.86, 0.171]	[0.86, 0.178]
district	[1.02, 0.189]	[1.02, 0.185]	[0.90, 0.010]	[0.90, 0.010]	[1.05, 0.265]	[1.05, 0.269]
household size	[1.00, 0.977]	[1.06, 0.000]	[1.15, 0.017]	[1.15, 0.020]	[0.96, 0.327]	[0.96, 0.334]
sex	[0.92, 0.481]	[0.92, 0.470]	[0.73, 0.140]	[0.74, 0.144]	[0.80, 0.326]	[0.80, 0.314]
age	[1.01, 0.009]	[1.01, 0.009]	[1.00, 0.882]	[1.01, 0.877]	[1.00, 0.710]	[1.00, 0.707]
marital status	[1.06, 0.303]	[1.06, 0.313]	[0.96, 0.372]	[0.96, 0.378]	[1.03, 0.545]	[1.03, 0.519]
education level	[0.91, 0.021]	[0.92, 0.022]	[1.02, 0.789]	[1.02, 0.813]	[0.89, 0.100]	[0.89, 0.100]
economic activity	[0.99, 0.592]	[0.99, 0.635]	[1.18, 0.426]	[1.19, 0.407]	[0.96, 0.831]	[0.96, 0.816]
access to electricity	[0.94, 0.687]	[0.94, 0.652]	[1.12, 0.539]	[1.12, 0.535]	[0.81, 0.306]	[0.81, 0.304]
household income	[1.00, 0.000]	[1.00, 0.000]	[1.00, 0.959]	[1.00, 0.886]	[1.00, 0.545]	[1.00, 0.312]
spend on house for farming	[0.56, 0.587]	[0.80, 0.802]	[——-, ——]	[——-, ——]	[0.00, 1.000]	[7.70, 0.306]
spend on land conservation	[2.61, 0.283]	[2.88, 0.223]	[——-, ——]	[——-, ——]	[——]	[——-, ——]
animal drawn vehicles	[2.55, 0.451]	[2.94, 0.330]	[——-, ——]	[——-, ——]	[——]	[——-, ——]
spend on scotch cart	[1.64, 0.694]	[1.94, 0.547]	[——-, ——]	[——-, ——]	[——-, ——]	[——-, ——]
spend on cattle	[0.17, 0.080]	[0.24, 0.041]	[——-, ——]	[——-, ——]	[——-, ——]	[——-, ——]
access to water	[0.88, 0.349]	[0.87, 0.326]	[0.97, 0.921]	[0.95, 0.860]	[1.01, 0.959]	[1.02, 0.951]
intercept	[0.12, 0.000]	[0.11, 0.000]	[0.03, 0.000]	[0.03, 0.000]	[0.12, 0.000]	[0.12, 0.000]

Variables: Urban/Rural, Household size Category, Sex, Age, Marital Status, Supplied Electricity, Economic Activity, Education level, Paid for Land conservation and improvements, Purchased Animal Drawn vehicles, Paid on Cattle, Access to own Water (within premises).

(p-value = 0.024), household size (p-value = 0.000), age of the household head (p-value = 0.000), the economic activity of the household head (p-value = 0.000), and access to electricity (p-value = 0.017). Consistent with the earlier survey years, the Firth Regression and Logistic Regression results for 2017/18 show minimal differences in estimated odds ratios and significance levels for the significant variables. The economic activity of the household heads reflects an AOR at 1.39 and a 95% CI of 1.16 to 1.67. The interpretation of the adjusted odds ratios is that unemployed household heads are 1.4 times more likely to fail to register their participation through spending on agriculture items. The result is plausible in that, household heads that are unemployed or not engaged in any form of activity have limited disposable income, and this weakens their purchasing power (including on agricultural-related purchases). In terms of access to electricity, the computed AOR is 0.77 and the true value lies between 0.63 and 0.95 for 95% CI. While the availability of electricity can leverage scaling; however, with current access, further concentrated within the urban setting, the results could indicate that increases in access to electricity are directed to the areas where the household basket of goods does not contain agriculture-related items. The comparison of both models across all three survey years indicates that the results are largely consistent, suggesting that separation, if present, did not substantially alter the key findings regarding the significant predictors and the direction of their effects.

Table 6. Adjusted Odds Ratios (AOR) generated for households spending on any one agricultural item – comparing Logistic Regression (LR) and Firth Regression (RF)

	Dependent variable: Spent any one Agric Product					
	2002/03		2010/11		2017/18	
Variable	LR[AOR, Sig.]	FR[AOR,Sig.]	LR[AOR, Sig.]	FR[AOR,Sig.]	LR[AOR, Sig.]	FR[AOR,Sig.]
urban/rural	[1.38, 0.087]	[1.37, 0.087]	[1.74, 0.040]	[1.73, 0.038]	[0.77, 0.023]	[0.77, 0.024]
zone	[1.22, 0.006]	[1.22, 0.006]	[1.26, 0.100]	[1.26, 0.096]	[0.94, 0.250]	[0.94, 0.254]
district	[0.89, 0.000]	[0.89, 0.000]	[0.93, 0.199]	[0.94, 0.203]	[0.96, 0.064]	[0.96, 0.064]
household size	[1.00, 0.984]	[1.11, 0.000]	[1.31, 0.001]	[1.30, 0.000]	[1.11, 0.000]	[1.11, 0.000]
sex	[0.76, 0.058]	[0.76, 0.054]	[0.61, 0.093]	[0.61, 0.097]	[0.85, 0.188]	[0.85, 0.186]
age	[1.00, 0.412]	[1.00, 0.412]	[1.01, 0.258]	[1.01, 0.259]	[1.02, 0.000]	[1.02, 0.000]
marital status	[1.23, 0.003]	[1.23, 0.003]	[1.01, 0.811]	[1.02, 0.800]	[0.95, 0.052]	[0.95, 0.052]
education level	[1.10, 0.021]	[0.91, 0.021]	[1.27, 0.025]	[1.26, 0.025]	[1.02, 0.631]	[1.02, 0.615]
economic activity	[0.96, 0.021]	[0.96, 0.020]	[1.52, 0.121]	[1.53, 0.117]	[1.40, 0.000]	[1.39, 0.000]
access to electricity	[0.92, 0.592]	[1.09, 0.558]	[0.84, 0.521]	[0.85, 0.539]	[0.77, 0.016]	[0.77, 0.017]
household income	[1.00, 0.033]	[1.00, 0.026]	[1.00, 0.488]	[1.00, 0.345]	[1.00, 0.687]	[1.00, 0.850]
spend on house for farming	[1.72, 0.508]	[2.05, 0.367]	[——-, ——]	[——-, ——]	[3.0e9, 0.000]	[5.58, 0.250]
spend on land conservation	[2.17, 0.490]	[2.95, 0.302]	[——-, ——]	[——-, ——]	——	[——-, ——]
animal drawn vehicles	[0.00, 0.999]	[2.10, 0.657]	[——-, ——]	[——-, ——]	——	[——-, ——]
spend on scotch cart	[3.01, 0.379]	[3.77, 0.243]	[——-, ——]	[——-, ——]	[——-, ——]	[——-, ——]
spend on cattle	[3.80, 0.004]	[3.95, 0.006]	[——-, ——]	[——-, ——]	[——-, ——]	[——-, ——]
access to water	[0.67, 0.004]	[0.66, 0.004]	[0.93, 0.862]	[0.89, 0.000]	[1.13, 0.322]	[1.13, 0.321]
intercept	[0.06, 0.000]	[0.07, 0.000]	[0.00, 0.000]	[0.00, 0.000]	[0.16, 0.000]	[0.16, 0.000]

Variables: Urban/Rural, Household size Category, Sex, Age, Marital Status, Supplied Electricity, Economic Activity, Education level, Paid for Land conservation and improvements, Purchased Animal Drawn vehicles, Paid on Cattle, Access to own Water (within premises).

4.3. Assessing the accuracy of model predictions

The Receiver Operating Characteristic (ROC) has been used to measure accuracy for diagnostic tests. Specifically, the use of ROC is to assess how well FR model fits the three HBS data sets in line with the proposed model specification. The study assessed the following metrics: Sensitivity and Specificity. The ROC curve is a plot of the true positive rates (TPR) versus the false positive rates (FPR) at various threshold values for defining a positive test result [7]. In line with ROC, the study limited the analysis to variables that had statistically significant relationships with the outcome variables (household participation in agricultural activities); the significance varied by model and survey year. The reflection of significance is based on the area under the curve (AUC). As illustrated in Figure 5 – in 2002/03 regarding the possession of of agricultural items – the ROC curve does not hover around the top left corner of the plot, a such, it reflects a relatively fair sensitivity and specificity.

In addition, in Table 7, the area under the curve varies by variable, with the lowest at 0.297 for urban/rural setting and the highest at 0.704 for zone. Generally, the model is considered a good fit in predicting participation of the household in agriculture, measured against their possession of agricultural items. Looking more closely at the individual AUC values, several variables demonstrate moderate predictive power. For instance, age and household size both have AUC values above 0.65, suggesting they are reasonably effective in discriminating between households that possess agricultural items and those that do not. Conversely, variables that include sex,

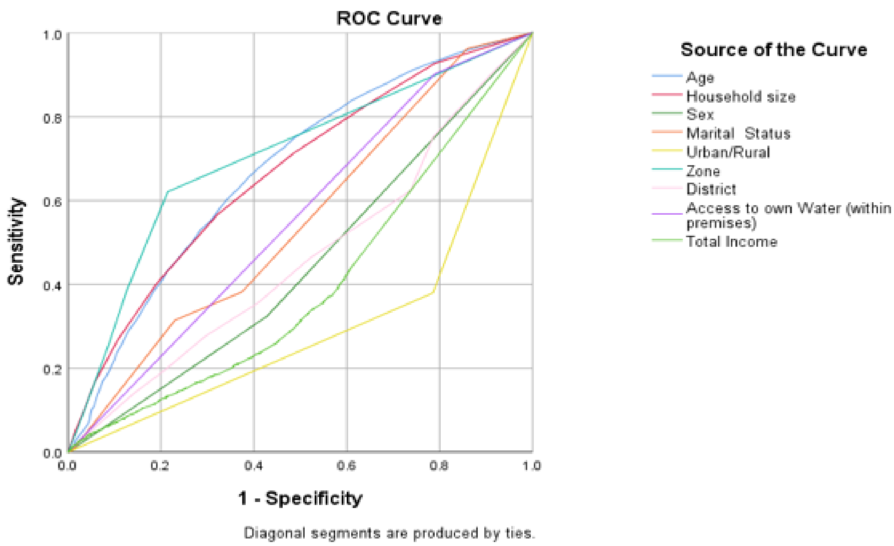

Figure 5. ROC Curve – Possess in one Agric item

district, urban/rural, and household income show AUC values below 0.5, indicating that these individual variables perform no better than random chance at predicting agricultural item possession. The high AUC of 0.704 for ’zone’ highlights its strong ability to differentiate between households with and without agricultural item possession, suggesting that ecological characteristics play a significant role in this outcome. The consistently low Asymptotic Significance (Asy. Sig.) values across all variables (all 0.000) indicate that the observed AUC values are statistically significant and not due to random chance, although the practical significance varies greatly depending on the AUC value itself. The 95% Confidence Intervals (CI-LB and CI-UB) provide a range for the true AUC value in the population; for example, the AUC for zone is estimated to be between 0.691 and 0.718 with 95% confidence.

Table 7. Area under the curve – possess any one agric item, HBS 2002/03

	Area under curve				
	Area	SE	Asy. Sig.^{b}	CI-LB	CI-UB
Age	0.673	0.008	0.000	0.659	0.688
Household size	0.665	0.007	0.000	0.650	0.679
Sex	0.448	0.008	0.000	0.423	0.463
Marital Status	0.549	0.008	0.000	0.432	0.463
Urban/Rural	0.297	0.007	0.000	0.283	0.311
Zone	0.704	0.007	0.000	0.691	0.718
District	0.462	0.008	0.000	0.447	0.478
Access to own water	0.556	0.008	0.000	0.540	0.572
Household income	0.397	0.008	0.000	0.381	0.412

Furthermore, as illustrated in Figure 6, the ROC curve does not hover around the top left corner of the plot, thus reflecting a relatively fair sensitivity and specificity. The observed position of the curve, away from this ideal corner, suggests that the model predicting whether a household sold any agricultural item has limitations in its ability to perfectly discriminate between households that sold and those that did not.

The above observation is corroborated by Table 8. In the table, the AUC varies by variable, with the lowest at 0.461 for household income and the highest at 0.614 for zone. Similarly, in predicting participation through trade registered by households, the model is considered a good fit. Through exploration at the individual AUC

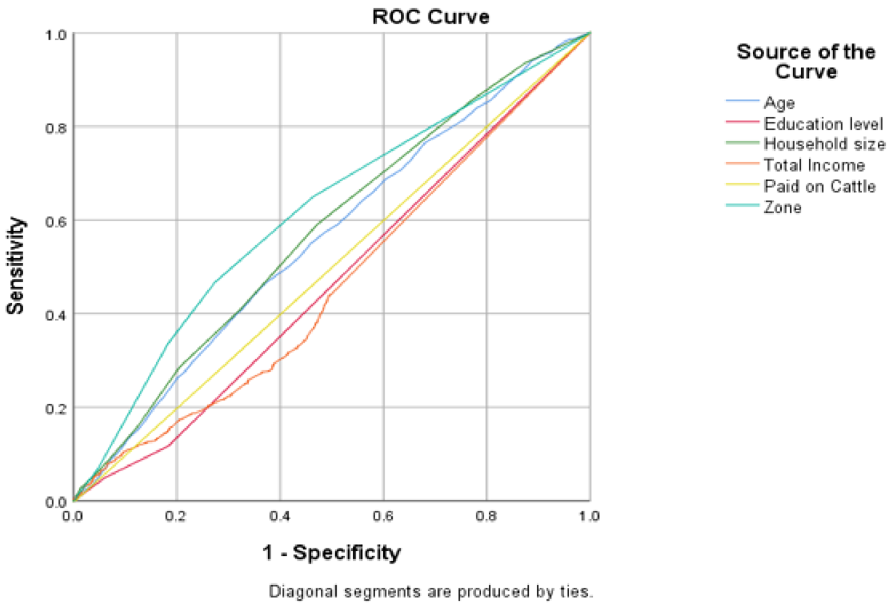

Figure 6. ROC Curve – Sold any one Agric item

values as demonstrated in the table, the highest AUC of 0.614 for zone suggests that geographical location has the strongest discriminatory power among the listed variables in predicting agricultural sales. However, an AUC of 0.614 is considered modest, indicating that zone alone is a weak predictor. Variables like household size and age also show AUC values slightly above 0.55, suggesting a very limited predictive capacity. Notably, variables such as education level and total income have AUC values below 0.5, implying that these variables are performing worse than random chance in predicting agricultural sales based on this metric. The Asymptotic Significance (Asy. Sig.) values, although mostly statistically significant (p ¡ 0.05, except for Exp. on cattle), should be interpreted alongside the practical significance indicated by the AUC values. The 95% CI-LB and CI-UB provide the likely range for the true AUCs in the population; for example, the AUC for zone is estimated to be between 0.538 and 0.580 with 95% confidence, reinforcing its limited predictive power.

Table 8. Area under the curve – sold any one agric item, HBS 2002/03

	Area under curve				
	Area	SE	Asy. Sig.[b]	CI-LB	CI-UB
Age	0.559	0.011	0.000	0.538	0.580
Education level	0.468	0.011	0.003	0.447	0.489
Household Size	0.574	0.011	0.000	0.553	0.594
Total income	0.461	0.011	0.000	0.440	0.482
Exp. on cattle	0.498	0.011	0.884	0.477	0.520
Zone	0.614	0.011	0.000	0.538	0.580

In relation to how the model predicts participation of households in agriculture relative to their expenditure, the ROC curve hovers below the top left corner of the plot, thus reflecting a relatively fair sensitivity and specificity (Figure 7).

The observed distance of the curve from this ideal corner suggests that the model struggles to effectively discriminate between households that spend on agricultural items and those that do not. This visual assessment is quantitatively supported by the AUC values presented in Table 9. The AUC for each variable represents the

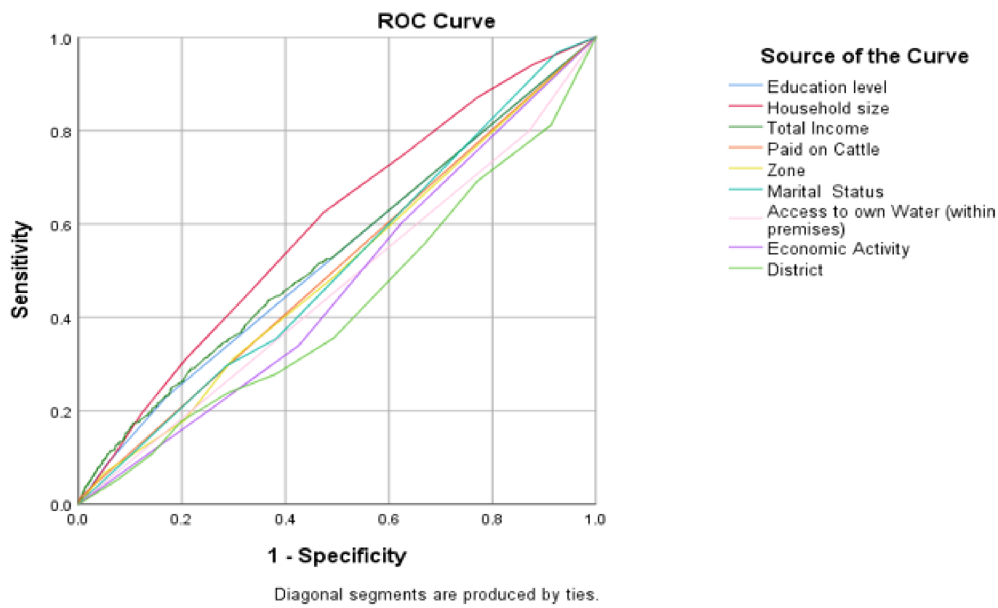

Figure 7. ROC Curve – Spent in one Agric item

probability that the model will rank a randomly chosen household that spent on an agricultural item higher than a randomly chosen household that did not spend. A value of 0.5 indicates the model performs no better than random chance, while a value of 1.0 represents perfect discrimination. As detailed in Table 9, the individual variables examined exhibit limited power in distinguishing between households that spend on agricultural items and those that do not.

Table 9. Area under the curve – spent on any one agric item, HBS 2002/03

	Area under curve				
	Area	SE	Asy. Sig.[b]	CI-LB	CI-UB
Education level	0.531	0.014	0.023	0.503	0.558
Household size	0.594	0.013	0.000	0.569	0.620
Total Income	0.537	0.014	0.006	0.509	0.565
Exp. on Cattle	0.506	0.014	0.680	0.479	0.533
Zone	0.498	0.014	0.883	0.471	0.525
Marital Status	0.506	0.013	0.653	0.480	0.532
Access to own water	0.464	0.014	0.008	0.436	0.492
Economic Activity	0.467	0.013	0.014	0.441	0.492
District	0.423	0.014	0.000	0.396	0.450

Interpreting the results in Table 9, we observe that the AUC for all variables is relatively low, with the highest value being 0.594 for household size. This suggests that, individually, household size is the most effective predictor among the variables listed, but its ability to discriminate between households that spend on agricultural items and those that do not is still only slightly better than random chance. Variables such as zone (AUC = 0.498) and *Exp.* on Cattle (AUC = 0.506) have AUC values very close to 0.5, indicating they provide little to no predictive power for this outcome. Furthermore, variables like access to own water, economic activity, and district have AUC values below 0.5, suggesting that using these variables alone would result in a model that performs worse than random guessing in identifying households that spend on agricultural items. While some variables show statistical significance (Asym. Sig. ¡ 0.05), the low AUC values indicate that this significance does not translate to practically useful predictive performance.

A similar analysis was conducted for HBS 2010/11. As depicted in Figure 8, the ROC curves for most variables approach the top left corner of the plot, indicating relatively high sensitivity and specificity.

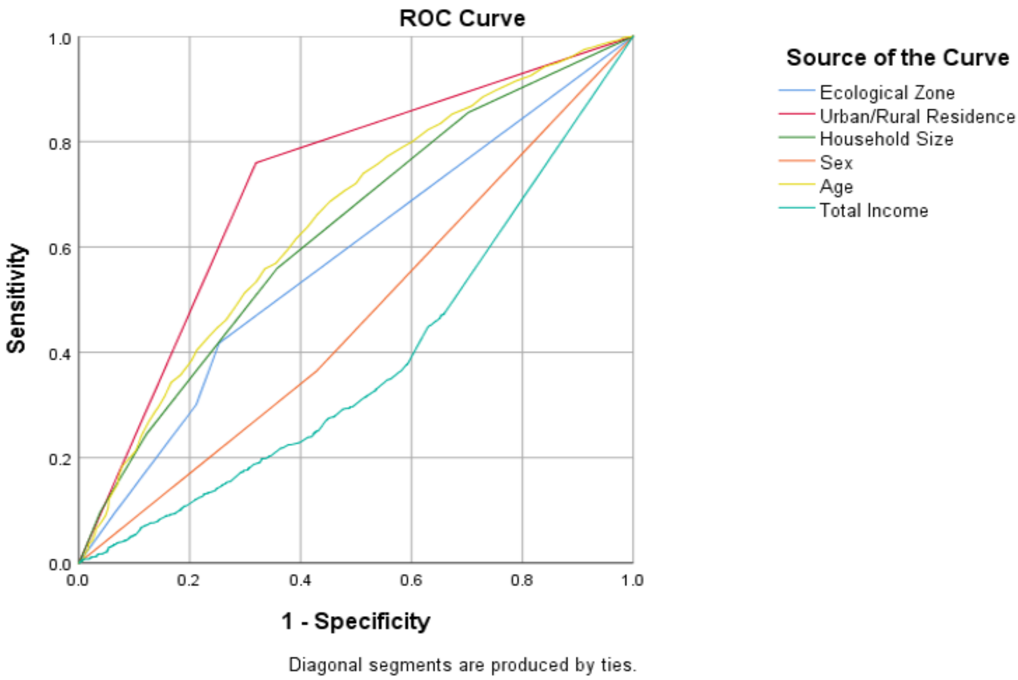

Figure 8. ROC Curve – Possess in one Agric item

This visual evidence suggests that the models have good discriminatory power for these variables. These observations are further corroborated by Table 10, which presents the AUC for each variable. The AUC quantifies the overall ability of each model to distinguish between the classes, with values closer to 1 indicating excellent discrimination. From this table (Table 10), it is evident that the variable urban/rural has the highest AUC at 0.720, indicating a good level of discrimination. Conversely, household income has the lowest AUC at 0.384, which suggests a limited ability of the model to distinguish between the classes for this variable. The remaining variables, such as age (0.653) and zone (0.576), demonstrate moderate discriminatory power, with their confidence intervals not crossing the 0.5 threshold, reinforcing their statistical significance.

Table 10. Area under the curve – possess any one agric item, HBS 2010/11

	Area under curve				
	Area	SE	Asy. Sig.^{b}	CI-LB	CI-UB
Age	0.653	0.011	0.000	0.631	0.675
Household size	0.631	0.011	0.000	0.609	0.653
Sex	0.468	0.012	0.007	0.445	0.491
Urban/Rural	0.720	0.011	0.000	0.699	0.741
Zone	0.576	0.012	0.000	0.553	0.599
Household income	0.384	0.011	0.000	0.362	0.407

The significance values (Asy. Sig.) for all variables are below 0.05, confirming that these AUCs are statistically different from 0.5 and thus meaningful. The narrow confidence intervals further support the reliability of these estimates. In summary, the ROC analysis, complemented by the AUC table, indicates that some variables - particularly urban / rural - offer strong predictive capabilities, while others, such as household income, are less informative within this model. This comprehensive assessment underscores the importance of considering multiple metrics when evaluating model performance. For household participation in trade (that is, selling at least one agricultural item), Figure 9 displays the ROC curves, which generally hover below the top left corner of the plot for most variables, suggesting a more moderate level of sensitivity and specificity compared to the model of possessing agricultural items. This visual observation is further supported by the AUC values presented in Table 11.

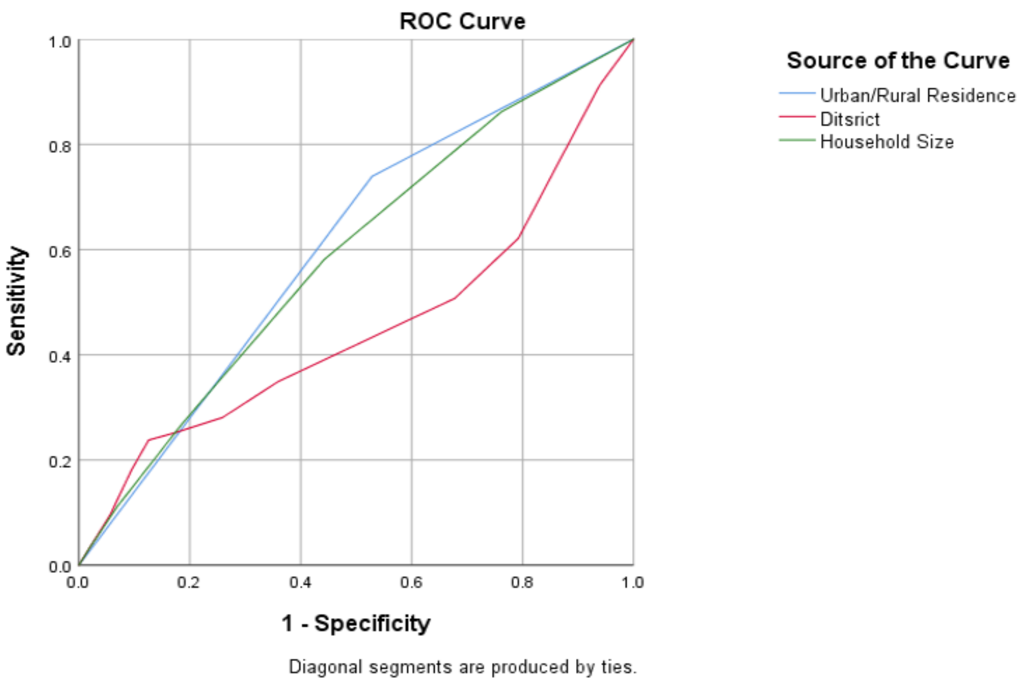

Figure 9. ROC Curve – Sold in one Agric item

In line with this table, the location of the household (urban/rural) exhibits the highest AUC at 0.605, indicating some discriminatory power, though notably lower than its AUC in the possession model, suggesting that location is less strongly associated with selling than possessing. The size of the household also shows a modest AUC of 0.587, indicating a similar level of predictive ability, with both urban / rural and the size of the household having highly significant p values (0.000) and confidence intervals greater than 0.5, confirming their statistically significant, albeit moderate, relationships. In contrast, the district has an AUC of 0.452, which is below 0.5, implying that the model performs worse than random chance in distinguishing between households that sell agricultural products based on this variable alone. Although its p-value (0.003) is statistically significant, this indicates a difference from 0.5 in the negative direction, indicating poor predictive power. Therefore, while some variables such as urban/rural and household size show some predictive ability, the overall fit of the model, particularly considering district performance, is at best moderate for some variables and poor for others, aligning with the less favorable visual pattern observed in the ROC curves.

Same as with ROC curves for possession and selling, which generally hover below the top left corner of the plot for most variables, suggesting a more moderate level of sensitivity and specificity compared to the model for possessing agricultural items, the ROC curve for spending on agricultural items also reflects varying levels of model performance (Figure 10). This observation in the ROC curve is corroborated by Table 12, which presents

Table 11. Area under the curve – sold any one agric product; HBS 2010/11

	Area under curve				
	Area	SE	Asy. Sig.[b]	CI-LB	CI-UB
Urban/Rural	0.605	0.015	0.000	0.576	0.634
District	0.452	0.019	0.003	0.416	0.489
Household size	0.587	0.015	0.000	0.557	0.618

the AUC values. While this table is introduced with the assertion that the model is considered a good fit, a closer examination of the AUC values reveals a more nuanced picture of discriminatory power across different variables.

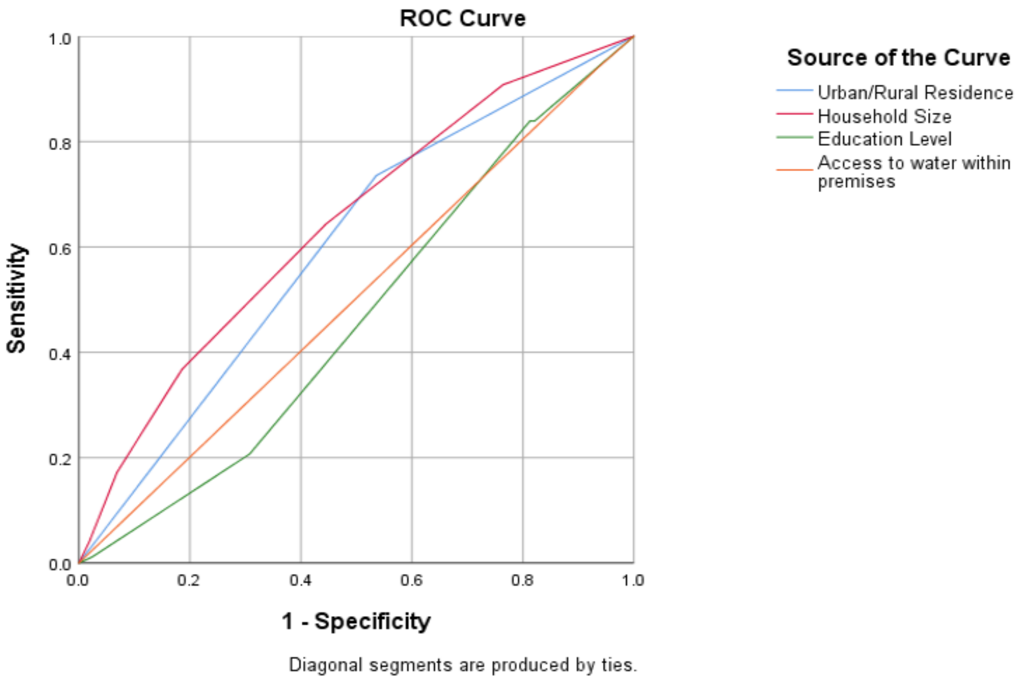

Figure 10. ROC Curve – Spent on any one Agric item

The AUC varies significantly, with the lowest at 0.467 for education level and the highest at 0.641 for household size. Specifically, household size demonstrates the strongest predictive ability with an AUC of 0.641, supported by a highly significant p-value of 0.000 and a confidence interval (0.600-0.682) well above 0.5, indicating a moderate positive association with spending and suggesting its ROC curve would be positioned highest above the diagonal. The urban/rural setting of the household also shows some modest discriminatory power with an AUC of 0.600, also statistically significant (p=0.000, CI: 0.559-0.640), indicating location plays a role and its ROC curve would be slightly lower than household size but still above the diagonal. In contrast, access to own water has an AUC of 0.503, very close to 0.5, with a non-significant p-value (0.903) and a confidence interval (0.459-0.546) that includes 0.5, indicating this variable performs no better than random chance and its ROC curve would be very close to the diagonal. Furthermore, education level exhibits the lowest AUC at 0.467, which is below 0.5, implying the model performs worse than random chance for this variable, despite a statistically significant p-value (0.037) indicating a difference from 0.5 in the negative direction, and its ROC curve would likely fall slightly below the diagonal. Consequently, the overall model fit for spending on agricultural items is moderate for variables that include household size and urban/Rural, but essentially non-existent for access to own water and poor for education level, visually reflected in the distribution of their respective ROC curves relative to the diagonal line.

Table 12. Area under the curve – spent any one agric item, HBS 2010/11

	Area under curve				
	Area	SE	Asy. Sig.[b]	CI-LB	CI-UB
Household size	0.641	0.021	0.000	0.600	0.682
Urban/Rural	0.600	0.021	0.000	0.559	0.640
Education level	0.467	0.020	0.037	0.427	0.507
Access to own water	0.503	0.022	0.903	0.459	0.546

Moving to the 2017/18 data, in relation to how the model predicts participation of households in agriculture relative to their possession of agricultural items, the ROC curve for this period generally hovers around the top left corner of the plot (Figure 11), thus reflecting relatively high sensitivity and specificity, indicating a stronger overall predictive performance compared to the 2010/11 spending model. This observation in the ROC curve is corroborated by Table 13, which presents the AUC values and asserts that the model is considered a good fit. The area under the curve varies significantly by variable, with the lowest at 0.332 for education level and the highest at 0.714 for age of the household head. Delving into the specifics of the same table, the age of the household head emerges as the strongest predictor of possessing agricultural items, boasting the highest AUC of 0.714. This is well above 0.5, with a highly significant p-value (0.000) and a confidence interval (0.697-0.731) comfortably above 0.5, indicating a strong positive association and suggesting its ROC curve would be closest to the top left corner.

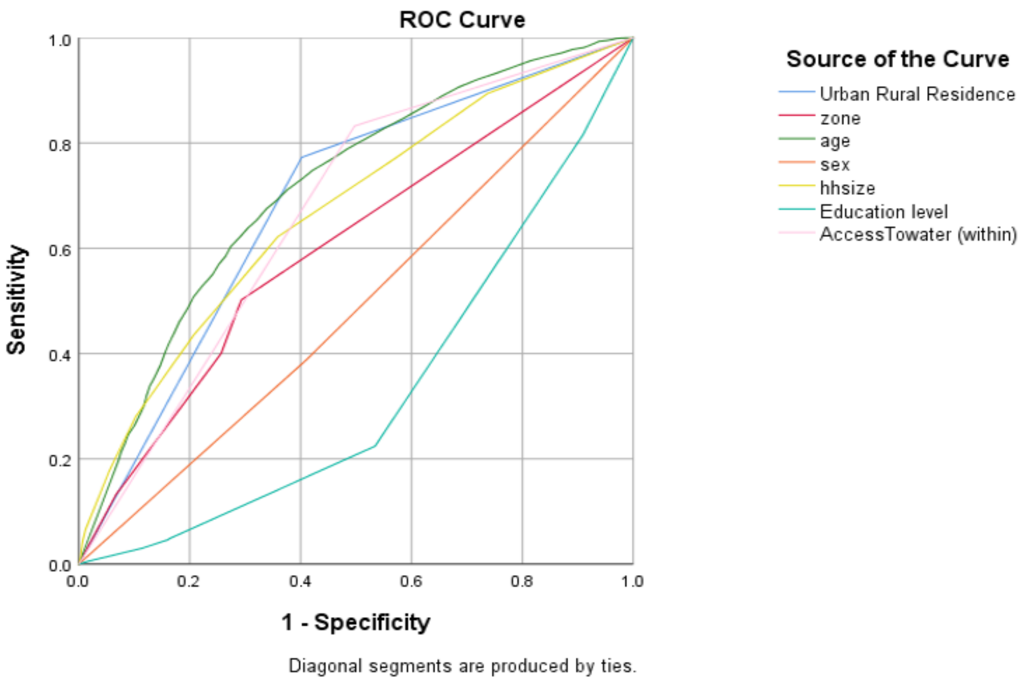

Figure 11. ROC Curve – Possess in one Agric item

The urban/rural residence of the household also shows significant predictive power with an AUC of 0.685, statistically significant (p=0.000, CI: 0.667-0.703), indicating that location remains a strong factor in 2017/18.

Table 13. Area under the curve – possess any one agric item, HBS 2017/18

	Area under curve				
	Area	SE	Asy. Sig.[b]	CI-LB	CI-UB
Urban/Rural	0.685	0.009	0.000	0.667	0.703
Zone	0.602	0.009	0.000	0.584	0.620
Age	0.714	0.009	0.000	0.697	0.731
Sex	0.489	0.010	0.242	0.470	0.508
Household size	0.669	0.009	0.000	0.652	0.686
Education level	0.332	0.009	0.000	0.314	0.350
Access to own water	0.667	0.009	0.000	0.649	0.686

Similarly, the size of the household and the access to its own water also show substantial discriminatory ability with AUC of 0.669 and 0.667, respectively, with highly significant p-values (0.000) and confidence intervals well above 0.5, indicating that larger households and those with access to their own water are more likely to possess agricultural items. These variables would also contribute to the position of the ROC curve, tending closer to the top left. The zone shows moderate predictive power with an AUC of 0.602, also statistically significant (p=0.000, CI: 0.584-0.620), suggesting that regional variations influence possession. In contrast, sex of the household head has an AUC of 0.489, very close to 0.5, with a nonsignificant p-value (0.242) and a confidence interval (0.470-0.508) that includes 0.5, indicating that gender alone is not a significant predictor and its ROC curve would be very close to the diagonal. Most strikingly, the level of education exhibits the lowest AUC at 0.332, significantly below 0.5, with a highly significant p-value (0.000) indicating a strong negative association. This suggests that higher education levels are associated with a lower probability of possessing agricultural items and its ROC curve would fall significantly below the diagonal. In summary, for 2017/18, the model for the possession of agricultural items shows generally strong performance for several key demographic and location variables, visually supported by the position of the ROC curve, with the notable exception of sex and a counterintuitive finding for the level of education. In terms of participation of households in agricultural activities assessed by their expenditure, the ROC curve generally hovers below the upper left corner of the plot for most variables (Figure 12), reflecting relatively fair sensitivity and specificity. This suggests that the model for spending on agricultural items in 2017/18 has limited discriminatory power. This observation from the ROC curve is corroborated by Table 14, which presents the AUC values. Although the table is introduced with the statement that the model is considered a good fit, the AUC values reveal a more modest level of predictive performance across the variables. The area under the curve varies, with the lowest at 0.462 for access to electricity and the highest at 0.584 for household size.

Examining Table 14 in more detail, the size of the household exhibits the strongest, although still moderate, predictive ability with an AUC of 0.584. This value is above 0.5, with a highly significant p-value (0.000) and a confidence interval (0.563-0.606) that is entirely above 0.5, suggesting a positive association with spending on agricultural items and indicating that its ROC curve would be the highest above the diagonal among the variables listed. The age of the household head also shows some limited predictive power with an AUC of 0.548, which is statistically significant (p=0.000, CI: 0.526-0.569), suggesting that age has a slight positive impact on spending. economic activity demonstrates a similarly modest AUC of 0.532, statistically significant (p=0.006, CI: 0.509-0.555), indicating that the economic activity of the household head has a weak positive association with spending on agricultural items. These variables would have ROC curves slightly above the diagonal. In contrast, urban/rural has an AUC of 0.471, which is below 0.5.

Although the p-value is statistically significant (0.014), indicating a difference from 0.5, the confidence interval (0.448-0.494) is entirely below 0.5. This suggests a slight negative association; that is, being in an urban area is associated with a lower likelihood of spending on agricultural items compared to rural areas, and its ROC curve would fall slightly below the diagonal. Similarly, electricity access has the lowest AUC at 0.462, also below 0.5, with a statistically significant p-value (0.001) and a confidence interval (0.439-0.485) entirely below 0.5. This indicates a negative association, where households with access to electricity are less likely to spend on agricultural

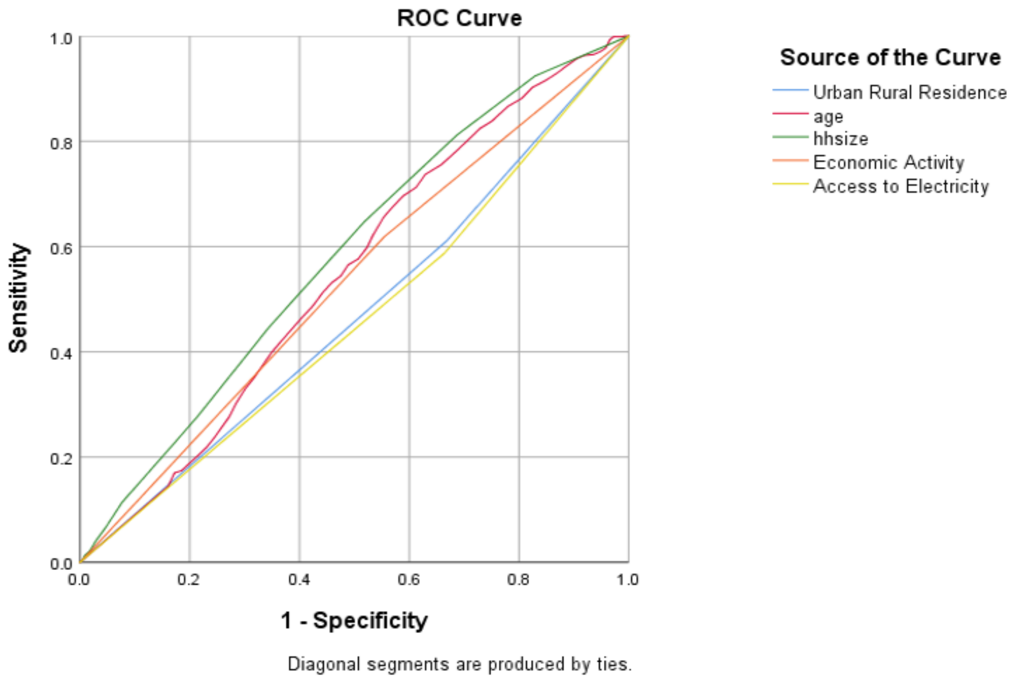

Figure 12. ROC Curve – Spent on any one Agric item

Table 14. Area under the curve – spent any one agric item, HBS 2017/18

	Area under curve				
	Area	SE	Asy. Sig.[b]	CI-LB	CI-UB
Urban/Rural	0.471	0.012	0.014	0.448	0.494
Age	0.548	0.011	0.000	0.526	0.569
Household size	0.584	0.011	0.000	0.563	0.606
Economic activity	0.532	0.012	0.006	0.509	0.555
Access to electricity	0.462	0.012	0.001	0.439	0.485

items, and its ROC curve would be the lowest below the diagonal. In summary, for 2017/18 spending data, the predictive power of the model is generally weak to moderate, with only household size, age, and economic activity showing a positive association with spending above the chance level. Urban / rural and access to electricity show a negative association, performing worse than random chance in predicting spending. The position of the ROC curve below the top left corner accurately reflects this overall pattern of limited discriminatory ability for most variables to predict the spending of agricultural items in 2017/18.

5. DISCUSSIONS

In this section, we discuss the results of this study and reflect on the choice of variables to predict agricultural participation in households. The section further considers how these variables, in conjunction with emerging climate change adaptation strategies, interact with ongoing agricultural interventions in Lesotho, mainly implemented to promote sustainable agricultural growth.

5.1. General Discussions

The effect of the variables on the specification varies with respect to the time and form of participation. To put this into context, in relation to households that participated in selling at least one agricultural product (that is, participated in the agricultural production chain), most statistical tests do not show a statistically significant effect. This is true for measurements conducted in 2002/2003, where the ecological zone, the size of the household, the age of the head of the household, the level of education of the head of the household, the income of the household and the expenditure of the family were the few variables reflecting significance. The midline survey (HBS 2010/11) reflects a decrease in the number of factors that explain participation by selling at least one agriculture product; noticeable effects are observed for household size, urban-rural setting, and district. In the 2017/18 HBS round, none of the selected variables reflected any statistical effect on influencing household engagement by selling at least one agricultural product. An important insight is the potential role of impacts of climate change, such as increased frequency and severity of droughts, unpredictable rainfall, and soil degradation, in influencing these participation patterns. Such environmental stresses can diminish the productivity and resilience of small farmers, thus affecting their market participation and asset ownership. To address these challenges, adopting climate-smart agricultural (CSA) practices, such as drought-resistant crop varieties, water harvesting, and soil conservation techniques, could be pivotal [23]. For example, promoting the use of drought resistant maize or sorghum, implementing water conservation techniques such as rainwater harvesting, and encouraging crop diversification could help farmers adapt to changing climatic conditions. Furthermore, insurance programs tailored for climate-related risks, such as weather-indexed crop insurance, could provide a safety net, reducing vulnerability, and encouraging sustained participation in agriculture. These strategies, although not directly measured in the data, are essential components of resilience building and should be integrated into policies to foster sustainable agricultural growth amid climate variability.

On a different dimension, the participation of households through spending on at least one agricultural product reflects a higher concentration of statistically significant variables. During the first survey round, the results suggested statistical significance for geographic settings, household size, marital status of the household head, education level of the household head, economic activity of the household head, household income, cattle spending, and access to water. Significant variables have declined in recent years, possibly indicating that climate change adaptation strategies, such as water conservation, access to climate information, and insurance, are not yet widespread, but could influence future participation. This trend is also evident in recent data, such as the 2022/23 Agricultural Production Survey in Lesotho, which highlights that the majority of household members were not engaged in agriculture, with only a small proportion participating for brief periods. Households investing in water harvesting or drought-resistant crops may be more resilient and thus more likely to sustain or increase their expenditure on agriculture. Policymakers should consider integrating these strategies into existing programs to improve household resilience and ensure continued participation in agricultural activities, especially in vulnerable ecological zones. Further analysis of household participation in agriculture, specifically focusing on possession of agricultural items or products, reveals a trend that aligns more closely with the initial observation regarding asset ownership. The data show that, after a decrease in most districts between 2002/03 and 2010/11, the percentage of households possessing agricultural items or products rebounded significantly in 2017/18. In many districts, the participation rate in 2017/18 exceeded the levels observed in 2002/03. This resurgence could be related to the increased adoption of climate adaptation measures, such as improved seeds, irrigation systems, or livestock management techniques, that support asset retention and productivity in the face of environmental stressors. It underscores the importance of policies that promote access to climate-resistant inputs and risk mitigation tools, which can help households maintain their agricultural assets and adapt to climate change. Analysis of participation by ecological zone reveals different patterns influenced by weather and terrain. In particular, the mountains zone, which historically showed high participation, experienced the most drastic drop in sales participation in 2017/18, potentially due to climate variability that affected crop yields and livestock. In contrast, increased investment in agricultural inputs in zones such as the Lowlands and Foothills may reflect adaptation efforts, such as drought-resistant crops or water management strategies. Integrating climate adaptation strategies into policy frameworks, such as subsidizing drought-tolerant seed varieties, promoting water conservation methods, and establishing insurance schemes, can improve resilience across ecological zones. This integrative approach would support households to maintain productive capacities despite environmental challenges.

5.2. Impact on Policy

In recent years, significant efforts have been made to develop agricultural policies and mobilise resources to address the multifaceted challenges facing the rural and agricultural sectors of Lesotho. The government, along with development agencies, has prioritised initiatives that promote agricultural productivity, food security, and diversification of livelihoods. However, this study emphasizes that understanding the geographical setting, such as ecological zones and terrain, remains crucial in the design of effective strategies. Recognizing these geographic differences allows policymakers to tailor interventions that are more context-specific, thus improving their effectiveness. In addition, incorporating gender and age-specific programs can help address the diverse needs of households, ensuring that vulnerable groups, such as women and the elderly, are better supported in participating in and benefiting from agricultural development efforts. The findings also underscore the urgent need to incorporate climate change adaptation strategies into Lesotho's agricultural policies. As climate variability increasingly threatens crop yields and livestock health, strategies such as promoting drought-resistant crop varieties, water conservation techniques, and risk mitigation through insurance schemes become essential components of sustainable agriculture. Integrating these measures into national programs can improve resilience among smallholder farmers, reducing their vulnerability to droughts, floods, and other climate shocks. For example, targeted subsidies for climate-smart inputs, investments in water harvesting infrastructure, and the expansion of crop and livestock insurance schemes can encourage farmers to adopt resilient practices and manage risks more effectively. Policymakers should consider specific, actionable steps to operationalize these strategies. Implementing targeted subsidies for drought-tolerant seeds and climate-smart technologies can facilitate adoption among smallholders. Investing in rural infrastructure, such as irrigation systems and water harvesting facilities, can improve water security in vulnerable zones. Developing comprehensive insurance schemes tailored to local risks can provide financial safety nets, incentivising farmers to invest in resilience-building practices. Furthermore, integrating climate adaptation into extension services and training programs will equip farmers with knowledge and skills to implement drought-resistant and water-saving techniques. Recognising the geographic disparities highlighted in this study enables the design of zone-specific interventions, such as soil conservation in mountainous areas and drought-resistant cropping in lowlands, ensuring that policies are equitable and effective. Although current data did not include direct measures of climate resilience practices, proactively incorporating these strategies into the larger policy framework will position the agricultural sector in Lesotho to better withstand the increasing impacts of climate change and promote sustainable and inclusive growth.

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