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LOGISTIC REGRESSION AND STATISTICAL INFERENCE FOR EVALUATING THE ECONOMIC BENEFITS OF CROP DIVERSIFICATION

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A R T I C L E I N F O

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Abstract
Crop diversification is gaining popularity as an approach to agricultural production that can benefit the profitability of the farm, the income stability of farmers, and sustainable resource use. The study employs logistic regression and statistical inference to assess the economic benefits of crop diversification. The quantitative research design involved secondary agricultural data with 405 observations and 23 variables, including monocropping, diversified cropping, income outcomes, and agricultural characteristics. Income differences and factors were compared using descriptive statistics, chi-square tests, and multivariable logistic regression with study-clustered standard errors. There was a positive income benefit for diversified cropping in 69.4% of the observations after provisional classification of the inconsistent outcome types. While there was considerable variability and income measurements were not harmonised, the mean income was higher for diversified cropping (115,790.87) than monocropping (56,693.30). The chi-square analysis revealed significant associations between soil fertility, agricultural inputs, water use efficiency, labour engagement, and price-related factors. Labour engagement was the only statistically significant predictor after adjustment by multivariable logistic regression (OR = 3.50; p = 0.038). The model showed an apparent ROC-AUC of 0.726 and a study-grouped cross-validation of 0.338, demonstrating poor predictive generalizability. In general, the economic gains of crop diversification were evident, though there were differences between agroecosystems. The results highlight the significance of the agricultural management conditions, reliable income measures, and additional validation for evidence-based agricultural diversification decisions.

Keywords: Crop Diversification; Logistic Regression; Agricultural Income; Economic Benefits; Statistical Inference

1. Introduction

Agriculture is an integral part of food security, rural livelihood, and economic development especially in areas where farming is a very important source of household income. In contrast, traditional farming practices with monocultures face problems of low soil fertility, climate volatility, and volatile prices and income. Crop diversification has as a result become a significant agricultural policy that integrates the growing of various crop species or mixes of crop species to better utilize resources, boost productivity and economic resilience. A diversified agriculture system can lower reliance on a single crop and enhance the sustainability of agriculture and livelihood. Past studies have focused on the role of agricultural diversification in improving productivity, profitability and sustainable resource management (Brosseau et al., 2021; Meena et al., 2018). In addition, diversification strategies can enhance the resilience of farming systems and minimize environmental shocks and production risks (Dardonville et al., 2020).

Crop diversification benefits not only farm production but also farm income, profitability, financial stability, and risk management. Diversified cropping systems are those that allow farmers to obtain income from various crops, which can decrease financial losses due to market or production shocks for a specific crop. In Bangladesh, diversification in the rice-based production system has shown potential to impact yield stability, profitability, and production risk (Assefa et al., 2021). Likewise, studies in India reveal the link between diversification of agriculture, transitions in farming systems and household income (Basantaray et al., 2022, 2024). Comparative studies on monocrops and diversified agriculture further illustrate the need to consider productivity in addition to profitability of farm operations (Horo & Singh, 2022). However, economic returns can vary with farm attributes, availability of resources, and household attributes. A study in Ghana finds a mixed link between crop diversification, farm net returns, and risk exposure to the economy (Adam & Abdulai, 2024). Further evidence suggests that diversification may be used to support rural adaptation and financial resilience in the face of a changing environment (Antonelli et al., 2022; Fabri et al., 2024).

The study of economic outcomes related to agricultural diversification is supported by statistical methods. Logistic regression is especially useful when the dependent variable is binary, like the question of whether diversified cropping proves to be more profitable than monocropping. This method attempts to determine the likelihood of an income gain for an agricultural and economic feature. Another way to examine association using statistical inference is to consider hypotheses, confidence intervals, and odds ratios. These techniques can detect the relationship between economic outcomes and explanatory factors, but should not be confused with a causal effect. Research into agricultural diversification has shown that the outcomes of diversification depend on the variability of rainfall, the conditions of the farm, and the economic position of the household (Kumari & Ramana Murthy, 2024; Makate et al., 2023). Therefore, logistic regression is a suitable model to explore variables that influence the probability of economic benefits from diversified cropping systems.

Agricultural research has been conducted extensively on crop diversification and its impact on productivity, sustainability and resilient responses to climate change and income improvement. Research has explored variations in diversification approaches among socioeconomic groups and their implications for agricultural livelihoods (Fujimoto & Suzuki, 2025). Recent studies have also emphasized the productivity, soil health, income generation and overall agricultural benefits of diversified rice-based cropping systems (Arvadiya et al., 2025). These studies, however, focus on different agricultural contexts and outcomes, and require a common statistical framework to account for the probability of positive income benefits and relevant agricultural features. The current study meets this analytical requirement by using logistic regression and statistical inferences with secondary agricultural data. Its value is in the careful analysis of income disparities between monocrops and diversified cropping systems, and the statistical identification of factors linked to a positive economic result.

This study aims to assess the economic advantage of crop diversification using logistic regression and statistical inference. In detail, the study seeks to determine the relative performance of monocropping and diversified cropping systems and explore agricultural and economic determinants of positive income benefits. In addition, it aims to quantify the direction, strength, and statistical significance of these associations by reporting odds ratios, confidence intervals, and appropriate hypothesis tests. Results helps inform evidence-based agricultural decision-making by providing information on the economic conditions of effective crop diversification strategies.

2. Materials and Methods

2.1. Research Design and Data Source

The study used a quantitative research design and the agricultural data were secondary data to assess the economic benefits of crop diversification. The data were gathered from agricultural investigations in various geographical localities and enabled statistical analysis of the differences that exist between the two systems of cropping, monocropping and diversified cropping (Durgesh 17, 2023).

2.2. Dataset Description and Study Variables

Agricultural characteristics, cropping systems and income outcomes data were collected, resulting in a total dataset of 405 observations and 23 variables. There were initially 267 classifications of positive income advantage and 138 nonpositive classifications for the binary dependent variable Income_advantage. Fourteen binary agricultural variables, such as access to credit, availability of resources, soil fertility, farm size, irrigation, production costs, etc., were used as explanatory variables.

2.3. Data Cleaning and Preprocessing

Data preprocessing steps involved checking missing values, consistency of variables, validity of income and binary

coding. The data set had no missing values, but some 14 values of income advantage were inconsistent and a few incomes were nonpositive, so they had to be verified. Income units and measurement periods were compared and study identifiers were kept to reflect observations from the same source.

2.4. Measurement of Economic Benefits of Crop Diversification
The economic benefits were assessed based on the reported income from monocropping and diversified cropping systems. Absolute income advantage was defined as the difference between diversified-crop and monocrop income. Relative income advantage was determined as a percentage of the monocrop income if income measurements were comparable and the baseline income was positive. Favorable economic outcomes were reflected in positive income differences.

2.5. Logistic Regression Model Development
A binary logistic regression was chosen as the analysis model to determine agricultural factors that affect positive income advantages. Income_advantage was the dependent variable and validated indicators of agriculture were the explanatory variables. Table 2 shows the regression coefficients interpreted as adjusted ORs and the selection of the predictors based on statistical suitability and multicollinearity assessment. Study-level dependence was taken into account when estimating the models.

2.6. Statistical Inference and Model Evaluation
The study examined agricultural characteristics and income outcomes using descriptive statistics. The relationships of categorical variables were analyzed by chi-square test and the set of odds ratios was estimated with 95% confidence intervals using logistic regression. The level of statistical significance was set at $p < 0.05$ and adjusted for clustering by the study level as appropriate. Receiver operating characteristic curve (ROC) and area under the curve (AUC) were used to assess model performance. For data management Microsoft Excel was chosen and for statistical analysis Python was chosen.

3. Results
3.1. Descriptive Characteristics of the Agricultural Dataset
The dataset consisted of 405 observations on agriculture of 67 study labels and 51 separate reference entries, representing various geographical regions and cropping systems. Fourteen binary variables were used to capture the agricultural characteristics, which characterized resource availability, production inputs, irrigation and agricultural conditions. The positive coding was applied to farm size with 21.7% of observations, soil fertility with 15.1% of observations and credit access with 9.9% of observations. The water use efficiency was positively coded for 32.1% of the records. There was a wide range of agricultural indicators recorded in the distributions. The descriptive statistics of the data set are presented in Table 1 where the main income indicators and some agricultural indicators are included.

Table 1. Descriptive Statistics of Agricultural and Economic Variables

Variable	Descriptive value
Total agricultural observations	405
Total variables	23
Distinct study labels	67
Monocrop income, mean	56,693.30
Monocrop income, median	21,036.00
Diversified-crop income, mean	115,790.87
Diversified-crop income, median	17,687.20
Farm size indicator = 1	88 (21.7%)
Soil fertility indicator = 1	61 (15.1%)
Credit access indicator = 1	40 (9.9%)
Irrigation facility indicator = 1	82 (20.2%)
Efficient water use indicator = 1	130 (32.1%)
Labour engagement indicator = 1	80 (19.8%)

Note. Income values are presented in the original dataset units, which have not been verified as comparable across

studies. Binary indicator frequencies describe recorded values, not necessarily measured farm-level prevalence.

3.2. Distribution of Income Advantages Across Crop Diversification Systems

The re-calculated income-advantage measure revealed 281 observations (69.4%) that reported increased diversified-crop income and 124 observations (30.6) that did not have a positive difference in income. The initial data set was used to categorize 267 positive and 138 nonpositive observations, which points out the influence of the 14 inconsistencies found during the validation. The re-calculated distribution suggested that the positive income differences were more common than the nonpositive differences in the records made. However, this distribution must not be taken to imply the percentage of agricultural households who gain through diversification. Figure 1 shows the distribution of positive and nonpositive income differences as per the recalculated outcome variable.

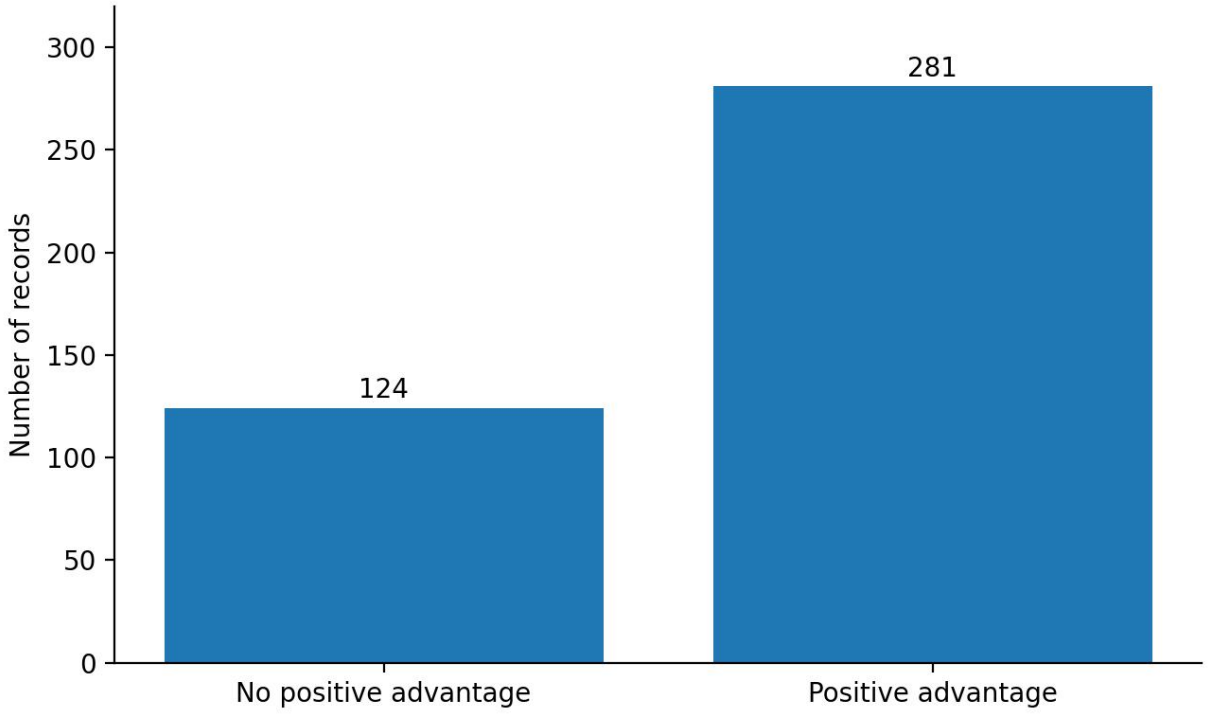


Figure 1. Distribution of Income Advantage Among Agricultural Observations

3.3. Comparison of Economic Outcomes Between Monocropping and Diversified Cropping

The descriptive analysis revealed a higher arithmetic mean in the case of diversified-crop income (115,790.87) compared to monocrop income (56,693.30). Nevertheless, the median diversified-crop income (17,687.20) was lower than the median monocrop income (21,036.00), which suggests that there were significant variations in patterns of distribution. The median within-record increase in income was positive at 320.00. The high income ranges and nonpositive values showed that there was a high degree of heterogeneity in the economic measurements reported. Since the observations were based on various studies, these numerical variations cannot be construed as harmonized currency-based profitability estimates. Table 2 gives a summary of the income distributions and within-record income differences in the agricultural data.

Table 2. Comparative Income Statistics of Monocropping and Diversified Cropping Systems

Statistical measure	Monocropping	Diversified cropping
Observations	405	405
Mean	56,693.30	115,790.87
Median	21,036.00	17,687.20
Standard deviation	179,159.83	496,442.36
Minimum	-1.00	-1.00
Maximum	2,381,405.00	5,957,969.00

Figure 2 presents the income distributions using boxplots with extreme observations suppressed visually to facilitate comparison of the central distributions.

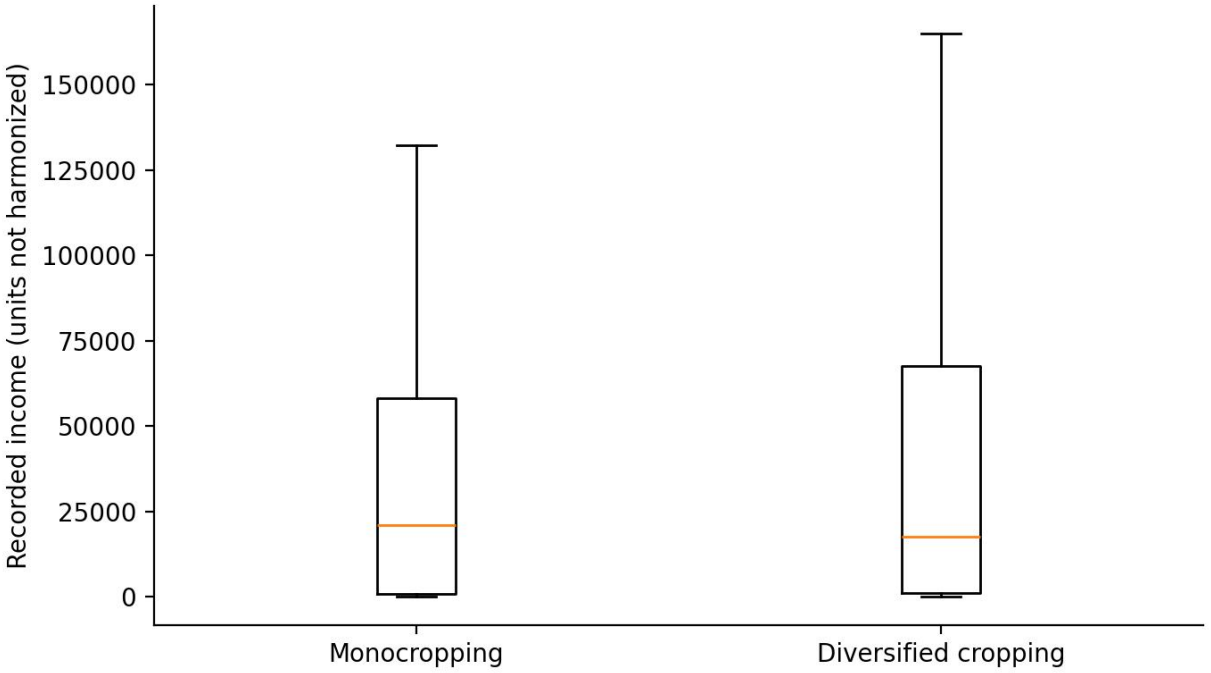


Figure 2. Comparison of Monocrop and Diversified Crop Income

3.4. Statistical Associations Between Agricultural Factors and Income Advantage

The chi-square tests conducted by Pearson were used to analyze unadjusted relationships between the 14 agricultural indicators and the recalculated binary income-advantage outcome. Significant associations were identified for soil fertility ($\chi^2 = 6.84$, $p = 0.009$), fertilizer or pesticide use ($\chi^2 = 7.80$, $p = 0.005$), efficient water use ($\chi^2 = 10.75$, $p = 0.001$), labour engagement ($\chi^2 = 6.61$, $p = 0.010$), and price-related factors ($\chi^2 = 5.09$, $p = 0.024$). Unadjusted associations between other agricultural indicators and income advantage at the 5% significance level were not statistically significant. The chi-square statistics and the significance level of all the agricultural indicators are shown in Table 3.

Table 3. Chi-Square Tests of Agricultural Factors Associated With Income Advantage

Agricultural factor	χ^2	p-value	Significant
Farm size	0.06	0.805	No
Soil fertility	6.84	0.009	Yes
Land-use efficiency	0.13	0.721	No
Credit access	0.20	0.652	No
Resource adequacy	1.72	0.190	No
Production cost	0.90	0.343	No
Certified seed	1.76	0.185	No
Fertilizer/pesticide	7.80	0.005	Yes
Irrigation facility	0.06	0.810	No
Efficient water use	10.75	0.001	Yes
Labour engagement	6.61	0.010	Yes

Seasonal crop shifting	3.65	0.056	No
Time availability	2.94	0.087	No
Price	5.09	0.024	Yes

3.5. Logistic Regression Results for Economic Benefits of Crop Diversification

A multivariate logistic regression was conducted on the 14 agricultural indicators to estimate the relationships with positive income advantage. Standard errors were grouped in terms of study label to deal with within-study dependence. The involvement in labour showed a statistically significant positive relationship with income advantage (OR = 3.50, 95% CI: 1.0711.41 = 0.038). There was a positive correlation between fertilizer or pesticide use (OR = 6.55) and its confidence interval was around unity (p = 0.058). There was an inverse adjusted correlation (OR = 0.20, p = 0.100) that was not statistically significant between efficient water use and the independent variable. The rest of the indicators did not have significant adjusted associations as well. The adjusted odds ratios and 95% confidence intervals of the multivariate logistic regression model were plotted in Figure 3.

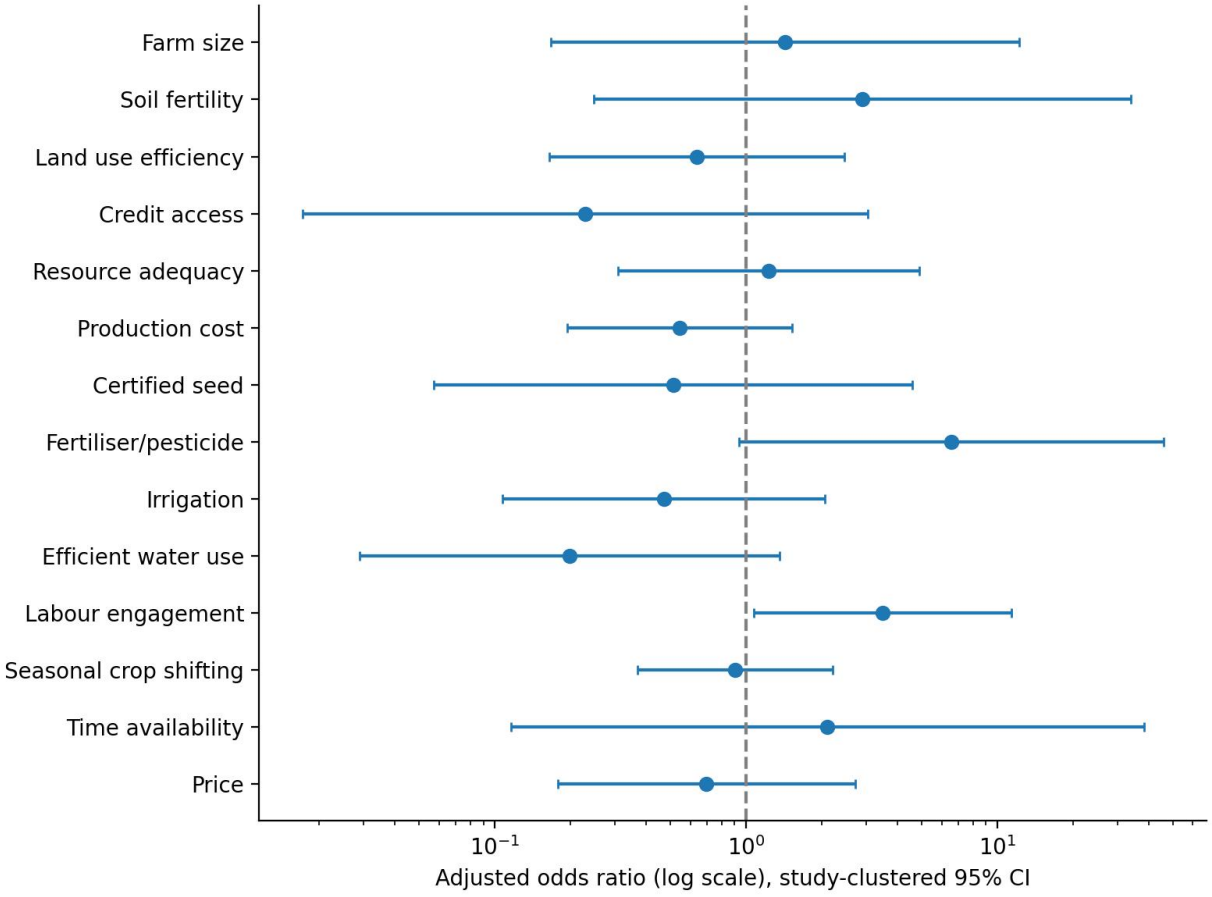


Figure 3. Logistic Regression Odds Ratios With 95% Confidence Intervals

Table 4 presents the estimated logistic regression coefficients, adjusted odds ratios, confidence intervals, and significance levels for the agricultural predictors.

Table 4. Logistic Regression Coefficients, Odds Ratios, Confidence Intervals, and Statistical Significance

Predictor	β	Adjusted OR	95% CI	p-value
Farm size	0.359	1.43	0.17–12.24	0.743
Soil fertility	1.066	2.90	0.25–33.93	0.396
Land-use efficiency	-0.451	0.64	0.17–2.46	0.513
Credit access	-1.476	0.23	0.02–3.05	0.264

Resource adequacy	0.206	1.23	0.31–4.91	0.770
Production cost	-0.612	0.54	0.19–1.52	0.244
Certified seed	-0.667	0.51	0.06–4.60	0.551
Fertilizer/pesticide	1.880	6.55	0.94–45.85	0.058
Irrigation	-0.755	0.47	0.11–2.06	0.316
Efficient water use	-1.617	0.20	0.03–1.36	0.100
Labour engagement	1.253	3.50	1.07–11.41	0.038
Seasonal crop shifting	-0.102	0.90	0.37–2.21	0.823
Time availability	0.744	2.11	0.12–38.30	0.615
Price	-0.363	0.70	0.18–2.72	0.602

Note. Estimates are from a binomial logistic regression model with study-clustered standard errors. OR = odds ratio; CI = confidence interval. The intercept is omitted from the table. Results are conditional on the provisional outcome recoding.

3.6. Logistic Regression Model Performance and Predictive Interpretation

Receiver operating characteristic analysis was used to assess model discrimination. The discriminatory power of the fitted model was moderate (apparent AUC = 0.726) for the data analyzed. If, however, the cross-validation is performed five-fold with the sources of study groups, the AUC is significantly reduced to 0.338. This difference represents the failure to generalize the apparent discrimination from studies not included in the training set. Results indicate that there is significant between-study variation and restricted transferability of the findings. Thus, the modified associations are to be taken with a grain of salt and the model is not yet well validated for prediction of economic benefits in new agricultural contexts. The ROC curve in Figure 4 shows the predictive ability of the model on the study groups that were not included in the model building process.

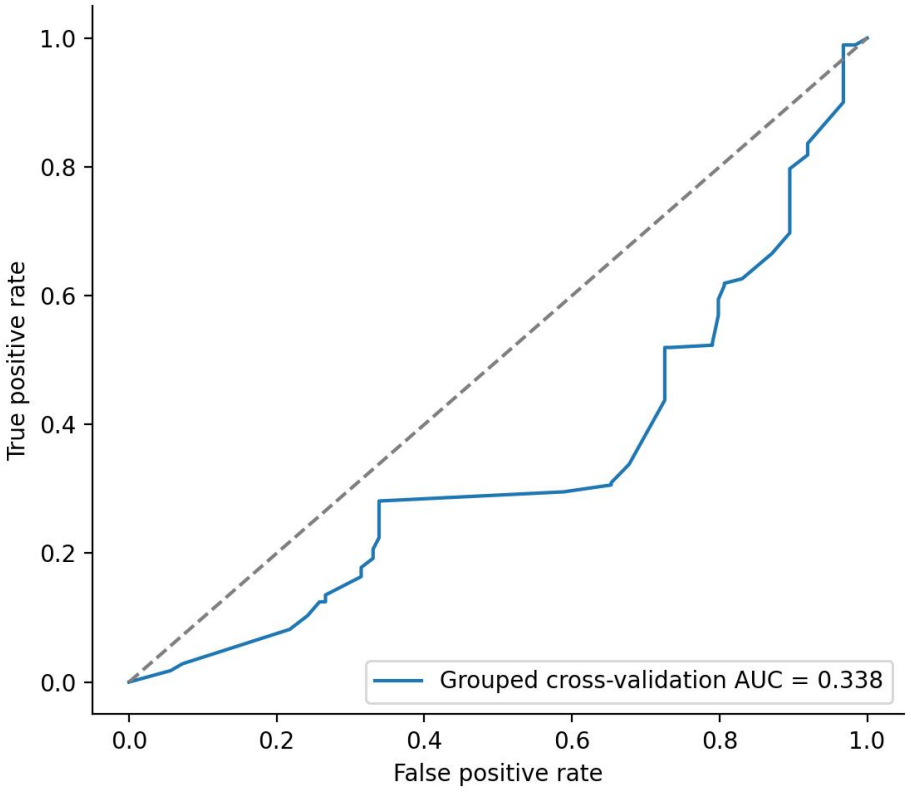


Figure 4. Receiver Operating Characteristic (ROC) Curve of the Logistic Regression Model

4. Discussion

The present study analyzed the economic benefits of crop diversification using descriptive statistics, chi-square tests and logistic regression. The results showed that 69.4% of agricultural observations had positive differences in income after the income-advantage indicator was recalculated. But significant differences were found between different income groups and agricultural features. After controlling for other predictors, labour engagement remained a statistically significant predictor of positive income advantage (OR = 3.50, p = 0.038), whereas the other predictors were not. The results indicate that the economic performance of diversification is related to various production factors in agriculture. Heterogeneity in farm income diversification and its connection to agricultural performance have also been highlighted in previous studies (Narayanamoorthy et al., 2025; Nilsson et al., 2022).

Descriptive results showed that diversified cropping had a higher mean income of 115,790.87 compared to monocropping with a mean income of 56,693.30. Median income was lower with diversified cropping, however, indicating that extreme observations skewed the average comparison. The median within-record difference was positive, suggesting positive results for a significant number of the observations. The results agree with those highlighting the potential profitability of diversified agricultural systems (Peddi & Reddy, 2023; Sánchez et al., 2022). However, the economic benefits are typically not easily translated to a general rule for all types of agricultural operations as diversifying require extra investments and management demands, as well as production limitations. These barriers have also been found in rice-based cropping systems (Rosenberg et al., 2025).

The chi-square analysis showed significant unadjusted associations for soil fertility, use of fertilizer or pesticide, efficient water use, labour involvement and price-related factors. But multivariable logistic regression found only labour engagement was significant at the 0.05 level. Use of fertilizer or pesticides showed a positive association, but it was not statistically significant. This distinction between individual associations and relationships estimated after adjusting for other agricultural characteristics points to the potential importance of distinguishing between these two types of associations. Previous research has shown that diversified farming systems come with a compromise between productivity, resource use and ecological impact (Guinet et al., 2023; Sun et al., 2021). Therefore, it is important to view agricultural inputs and conditions of agriculture as potentially interrelated factors rather than separate factors affecting profitability.

The results tend to confirm the existing evidence that crop diversification can be a partial solution to improving agricultural incomes, but with varying results in different production environments. Switching from the traditional rice system to other cereals offer benefits for farmer incomes and mitigate production losses due to climate change in India (Wei et al., 2025). Likewise, crop switching has been shown to create income opportunities in farming in China (Xie et al., 2023). Crop diversification among smallholder farmers also has welfare implications which have been emphasized by studies in Nigeria (Baiyegunhi et al., 2022). However, climate change and climatic variability can affect diversification decisions and impact farmers' households and make it difficult to compare them directly between agricultural regions (Chuang, 2019).

The results emphasize the need to take into account agricultural management characteristics when assessing strategies for diversification. The positive relationship between labour engagement indicates that availability and management of labour resources important for economic outcomes associated with diversification. Therefore, the labour needs, availability of resources and local production situations must be taken into account by anyone pursuing a strategy of diversified farming through agricultural extension and/or policy support. Agricultural diversification can also help towards the broader sustainability goals by enhancing production resilience and decreasing reliance on a single crop. Rice diversification has been demonstrated to contribute to agricultural sustainability and resilience in rice-production systems in the world (He et al., 2023).

The secondary data were taken from different studies which lead to variations in income measurement, geographical factors, and agricultural practices. The outcome classifications were inconsistent and outcomes were not positive, necessitating a check of the entries. In addition, the apparent ROC-AUC of 0.726 dropped to 0.338 in the study-grouped cross-validation, suggesting that the model's performance is not generalizable. Association between diversification and income improvement cannot be established using observational associations. Harmonized longitudinal farm-level data, valid external data, and farm-level income measures would be useful for future research to improve economic inference.

5. Conclusion

The present study was conducted to assess the economic returns of crop diversification with the aid of descriptive statistics, statistical inferences and binary logistic regression. The results showed that 69.4% of the agricultural observations had positive income differences between diversified and monocropping systems, suggesting that agricultural diversification offer economic benefits. While diversified cropping had the highest mean income, differences in median values and the high income variability did reveal the heterogeneous nature of economic outcomes across agricultural settings. Soil fertility, use of fertilizer and/or pesticide, efficient use of water, labour involvement, and price-related factors were found to be significantly associated using chi-square analysis. Multivariable logistic regression, however, showed that only labour engagement was a statistically significant adjusted predictor of positive income advantage, highlighting the possible significance of agricultural workforce availability and management capacity. The model had moderate apparent discrimination (ROC-AUC 0.726), but poor performance in the study-grouped cross-validations, showing low generalizability across agricultural contexts. In addition, income measurement was variable, study characteristics and observational data were variable, and causal interpretation was limited. The results indicate that there could be some economic opportunity for crop diversification, but this may be limited by

agricultural resources, production limitations, and local management situations. Further studies could include harmonized farm-level income information, longitudinal observations and good external validation to enhance statistical reliability. Overall, the study adds to the agricultural economics literature by highlighting the usefulness of logistic regression in studying the income benefits of agricultural diversification and in evidence-based agricultural decision-making.

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