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Exploring the impact of diversification on agricultural commercialisation in North Karnataka, India: K-means clustering and regression analysis approach

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ABSTRACT

This study delves into the pivotal role of agricultural diversity in shaping the commercialisation of agriculture in northern Karnataka, India. While diversification is often viewed as a risk mitigation strategy, its influence on the transition toward market driven agriculture is critical for rural transformation. The research was conducted across two distinct regions, Cluster-I (Dharwad and Gadag) and Cluster-II (Belagavi and Bagalkote) based on the Gross Irrigated Area (GIA). Data were gathered from 240 farm households through meticulously designed personal interviews during the 2022–23 agricultural season. The analysis employed a combination of descriptive statistics, K-means clustering and the Herfindahl-Hirschman Index (HHI) to quantify diversification, as well as the Household Crop Commercialisation Index (CCI) to assess commercialisation. The clustering results revealed stark contrasts between the two regions, with Cluster-I exhibiting higher level of crop diversification and lower-level commercialisation (HHI: 0.45) and Cluster-II demonstrating more market-oriented farming practices coupled with a lower degree of diversification (HHI: 0.66). To determine the causal impact, a Regression Adjustment (RA) model was employed, which confirmed that diversification significantly enhances commercialisation levels. The study highlights that diversification and commercialisation are complementary pathways for sustainable agricultural development. Therefore, region-specific policies focusing on irrigation expansion, promotion of diversified cropping systems, market infrastructure and institutional support are essential for strengthening resilient and market-oriented agriculture in North Karnataka.

Keywords: Crop commercialisation index, Farm households, Gross irrigated area, Herfindahl hirschman index, Regression adjustment

In recent decades, agricultural commercialisation, defined as the shift from subsistence-oriented production to market-oriented farming, has intensified globally. While expanding markets for high-value crops frequently create economic incentives for commercialisation (Barrett *et al.* 2001), the dynamic relationship between market integration and farm-level diversity remains non-linear and highly complex. As global climate regimes shift unpredictably and the costs of synthetic cultivation inputs escalate, conventional, input-heavy monocropping practices have become economically and ecologically unsustainable.

Recent scientific syntheses underscore that transitioning toward diversified agroecosystems is no longer a choice but an absolute ecological necessity for building climate resilience. A landmark systematic review of 134 diversified systems globally reveals that these practices increase an average yields by 20–38% than rigid monocropping, while simultaneously enhancing the soil organic carbon by a median of 9% (Sridhar *et al.* 2026). Furthermore, these diversified systems strategically disrupt pest and disease life cycles by fostering complex habitats that increase natural enemy populations. Consequently, this biological control mechanism reduces the farm's dependence on costly synthetic chemical inputs by up to 40%, optimising both environmental safety and smallholder profit margins (Beillouin *et al.* 2021).

In the Indian agrarian context, excessive and unregulated commercialisation has frequently acted as a double-edged sword. While driving immediate cash income, it has promoted strict crop specialisation, leading to severe natural resource degradation (Pingali 2012). Decades of cereal-centric systems, particularly the intensive wheat–paddy and paddy–paddy rotations, have triggered critical groundwater depletion, declining soil organic matter and widespread micronutrient deficiencies across major agricultural tracts. This ecological strain severely threatens the structural viability of smallholder production.

Given that approximately 86% of operational

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landholdings in India are classified as small and marginal (<2 ha), the income generated from resource-stressed monocultures is increasingly insufficient to sustain rural livelihoods or ensure household income stability (Sivaraman *et al.* 2024). Within this vulnerable socio-economic framework, agricultural diversification is conceptually defined as the strategic reallocation of a farm's land, labour and capital resources into a broader, more heterogeneous mix of activities to optimize net returns and minimize production risks (Joshi *et al.* 2004). According to the conceptual frameworks advanced by Vernooy (2022), this transition operates on a theory of change where sustained crop diversification builds ecological redundancy. This structural redundancy allows smallholders to generate multiple, simultaneous livelihood benefits, such as stabilised income streams and strengthened innovative capacity, thereby accelerating the wider societal transition toward sustainable, climate-resilient food systems. Transitioning away from staple monocultures toward integrated high-value horticulture, multi-tier agroforestry and livestock components has therefore emerged as a core strategy. This approach not only buffers farmers against localised crop failures but also acts as an expedient vehicle for enhancing productive rural self-employment and labour absorption (Kumar *et al.* 2022).

While agricultural transformation is occurring across the Indian subcontinent, its spatial dynamics vary significantly by agro-climatic zone, even within a single state. Recent empirical evidence from coastal Karnataka underscores a rapid spatial and temporal shift in cropping patterns, characterized by a transition from traditional, labour-intensive paddy cultivation to highly lucrative perennial commercial crops such as rubber and arecanut (Kochi and Rode 2026). Concurrently, investigations into the dynamic rural-urban interface of Bengaluru demonstrate that crop diversification can function as a highly viable commercial strategy when backed by robust metropolitan consumer demands and direct market access (Thejashree and Umesh 2022).

However, a distinct and critical research gap persists regarding these dynamics within the geographically unique, semi-arid and transitional dryland zones of North Karnataka. Unlike the humid coastal belt or the urbanised southern periphery, North Karnataka is constrained by severe biophysical pressures, lower baseline irrigation infrastructure and high vulnerability to drought. It remains unclear how smallholders in these drylands navigate the trade-offs between diversification as a risk-mitigation tool and commercialisation as an income maximiser.

This study addresses this empirical gap by analysing farm-level data from North Karnataka. By utilising a robust methodological framework combining K-means clustering to segment households (based on irrigation profiles, agricultural productivity and economic endowments) and Regression Adjustment (RA) models, this research provides an objective, context-specific assessment of how crop diversification actively drives, shapes and sustains agricultural commercialisation in India's vulnerable semi-arid drylands.

MATERIALS AND METHODS

The study relied on primary data from the agricultural year 2022–23, collected from 240 sample respondents selected through a multistage purposive random sampling method. In the first stage, four districts in northern Karnataka (India) were purposively chosen based on their Gross Irrigated Area (GIA). To capture the absolute variation across the region's irrigation profile, the top two districts having highest GIA and the bottom two districts having lowest GIA were chosen for data collection, establishing a robust baseline contrast. This resulted in their initial classification into two clusters. Dharwad (88,377 ha, 1.46% of Karnataka's total GIA) and Gadag (1,24,088 ha, 2.05% of Karnataka's total GIA) were classified into "Cluster-I", while Belagavi (863,542 ha, 14.24% of Karnataka's total GIA) and Bagalkote (425,799 ha, 7.02% of Karnataka's total GIA) were placed in "Cluster-II" (Karnataka State at a Glance 2021–22, Government of Karnataka). In the second stage, two talukas from each district were purposively selected, one with the highest and the other with the lowest GIA. In the third stage, from each taluka, three villages were randomly chosen. Finally, 10 farm households from each village were selected using a stratified approach: six small, three medium and one large farmer. This stratification was based on the proportionate distribution of landholding categories in the study area to ensure the representativeness of the 240 households. As a result, the sample consisted of 240 respondents, drawn from 24 villages across eight talukas in four districts of northern Karnataka, India. Data were collected through personal interview method using a pre-tested, structured interview schedule that covered socio-economic indicators, cropping pattern, input use and marketed surplus.

Cluster analysis: K-means cluster analysis is a measurable, unsupervised, non-deterministic, iterative technique for gathering the diverse observations into clusters, it is the least complex unsupervised learning calculations known for its speed, ease and convenience (Gudvalli *et al.* 2017). Here K-means algorithm was used to cluster the farmers to notice the commercialisation across the "Cluster-I" and "Cluster-II". Variables used for clustering are percentage of area under irrigation, main product yield, total annual income of farm households and source of irrigation.

Here, R software package version 4.3.1 was used to find the optimum number of clusters using elbow method. In the graph, the point at the bend or elbow was taken as the optimum number of clusters. The curve in graph showed the decline in within cluster sum of squares differences, as the number of cluster increases provides the best solution (Oyelade *et al.* 2010). A higher silhouette coefficient indicates better-defined clusters. The cluster plot visually depicts the clusters formed by the K-means algorithm for the study area. Each point represents an individual data point and different colours or markers denote different clusters.

Equation 1 depicts the algorithm with a segment of Euclidean distance:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \| x_i^j - c_j \|^2 \quad (1)$$

Where $\| x_i^j - c_j \|$ computes Euclidean distance (Owino *et al.* 2020). The Euclidean distance estimates the weights of data observation; k, Number of clusters; n, number of observations; j, Minimum number of clusters; I, Minimum number of observations; x_i, Euclidean vector for any i^{th} observation; c_j, Cluster centre for any j^{th} cluster known as cluster centroids; K, Means algorithm for classification takes each cluster's center by the mean value of the objects (observations) in the cluster. The normalised data is used while running the algorithm.

Herfindahl-Hirschman Index (HHI): To study the extent of crop diversification, HHI as used by Pal and Kar (2012) was used in the present study:

$$HHI = \sum_{i=1}^{N} P_i^2 \quad (2)$$

Where, N, Number of crops cultivated; P_i, Area under i^{th} crop in total area of cultivation.

The index reaches value of one under total specialisation and moves towards zero for increasing diversification. Hence, the range of index is zero to one. The farmers with index value less than 0.5 is grouped under zero category indicating diversified farmers and farmers with value more than 0.5 are taken under category one, indicating farmers growing monocrops.

Crop Commercialisation Index (CCI): In the present study, household CCI was used to estimate the extent of commercialisation. The CCI is an important metric used to assess the degree to which crops produced by a farmer are sold in the market rather than consumed by the household. This index is crucial for understanding agricultural commercialisation and its impact on rural economies and household welfare. CCI is defined as the proportion of the output which has been sold (Braun and Kennedy 1994, Muriithi and Matz 2015).

The most commonly used formula for the CCI is:

$$CCI = \frac{\text{Gross value of crop sales}_{hhi}}{\text{Gross value of all crop production}_{hhi}} \times 100 \quad (3)$$

Where hhi, i^{th} household.

The value of zero indicates that the farmer is totally subsistence and the value closer to hundred depicts that the farmer is highly commercialised.

Regression Adjustment (RA) method: To assess the effect of agricultural diversification on commercialisation of agriculture, RA method was used. Here, agricultural diversification is taken as a non-randomised treatment, where zero indicates specialised farm households and one indicates diversified farm households. The diversified farm households could differ significantly on potentially confounding factors, compared to specialised farmers. This difference leads to biases, while estimating the impact of agricultural diversity on commercialisation of agriculture. Even the randomised treatment assignment may not justify the bias (Freedman 2008). Henceforth, RA model is used, most commonly utilised and can be very efficient in estimating the effects by minimizing the bias (Myers and Thomas 2010). Wooldridge and Negi (2018) in their joint work on RA stated that RA possibly improves precision by regressing on covariates that predict the outcome.

Regression Adjustment (RA) is interested in estimating the Average Treatment Effect on the Treated households (ATET), defined as the average difference in commercialisation (outcome) with and without the diversification. Following Horner and Wollni (2011), the ATET is written as:

$$ATET = E\{Y_{iD} - Y_{iN} | T_i = 1\} \quad (4)$$

$$= E(Y_{iD} | T_i = 1) - E(Y_{iN} | T_i = 1) \quad (5)$$

Where E{.}, Expectation operator; Y_{iD}, Predicted outcome (commercialisation) for diversified farm household I; Y_{iN}, Predicted outcome of the same household under specialised situation; T_i, Treatment groups (diversification) status taking one for diversified (treated) and 0 for specialised.

However, while the extent of commercialisation for the diversified household from the diversification group, i.e. E $(Y_{iD} | T_i = 1)$ can be observed from the data, the counterfactual outcome E $(Y_{iN} | T_i = 1)$, commercialisation of the same household being specialised cannot be observed. RA is used to solve this problem (Horner and Wollni 2011).

The R software package version 4.3.1 was used to perform RA technique for analysing the relationship between diversification and commercialisation. RA technique creates separate linear regression models for treated and untreated observations, then predicts covariate-specific outcomes for each subject for each treatment status. These predicted average outcomes for each subject and treatment level reflects the Potential Outcome Mean (POM). The difference of these averages provides estimates of ATEs. The ATETs are obtained by limiting the computation of means to the subset of treated individuals. RA equation is expressed as following by Manda *et al.* (2018):

$$ATET_{RA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_D(X, \delta_C) - [r_N(X, \delta_N)] \quad (6)$$

Where n_A, Number of diversified farm householdS; r_i (X), Regression model for commercialised farm households with covariate X and estimated parameters δ_i $(\alpha_i \beta_i)$.

RESULTS AND DISCUSSION

Results of K-means clustering algorithm: The elbow method graph illustrates the relationship between the number of clusters (K) and the total Within-cluster Sum of Squares (WSS). As the number of clusters increases, WSS decreases sharply. A distinct 'elbow' was observed at K=3, indicating that a three-cluster model could mathematically explain the variance. However, a two-cluster configuration was ultimately selected for this study (Fig. 1). This decision was guided by an average silhouette coefficient of 0.60

for the two-cluster solution indicates clear, well-defined groups, that suggests two-clusters offer a more meaningful separation of the data compared to a three-cluster model, which showed less distinct clusters. Thus, the two-cluster model aligned effectively with the study's objectives and provides clear, actionable insights. The cluster plot, which displayed the results of the K-means clustering algorithm with data points plotted along two dimensions, likely the principal components. It showed that Cluster-I (in red) and Cluster-II (in blue) are distinctly separated, indicates a clear division of the data into two groups (Fig. 2). This analytical approach directly echoes the work of Thejashree (2022), who utilised the K-means clustering algorithm to segment farming households and evaluate variations in agricultural commercialisation across the rural-urban interface. The study by Swain *et al.* (2024) on crop selection, underscores the efficacy of K-means clustering as an unsupervised learning mechanism to map complex interactions between environmental inputs and agricultural outcomes, transforming raw statistical data into structured, decisive categories.

Outcomes of the K-means clustering algorithm applied to data from both Cluster-I and Cluster-II is given in Table 1. Cluster-I, representing the less GIA, was characterized by younger respondents (-0.51), slightly lower proportion of males (-0.97), fewer years of education (-0.31), smaller family units (-0.16), slightly larger landholdings (0.16), lower social participation (-0.18), lower agricultural assets (-0.13), reduced fertiliser (-0.18) and pesticide usage (-0.22) and significantly lower Crop Commercialisation Index (CCI) values (-0.82). Farmers in less irrigated area generally depend on rainfall and tend to cultivate low-risk field crops with lower input application in order to minimise production losses under uncertain moisture conditions. Consequently, lower fertiliser and pesticide use in Cluster-I reflects lower crop intensification and reduced adoption of improved production technologies. In addition, the predominance of medium and deep black soils in certain parts of Cluster-I encouraged cultivation of traditional field crops such as sorghum, pulses and oilseeds, which generally require comparatively lower external inputs and are less market-oriented. The comparatively lower educational status and social participation further suggest weaker institutional linkage and reduced exposure to improved production and marketing practices.

Conversely, Cluster-II, representing the more GIA, consisted of relatively older respondents (0.52), a higher proportion of males (0.98) and better educational attainment (0.32). The respondents had comparatively larger family units (0.23), smaller landholdings (-0.14), higher social participation (0.21) and greater ownership of agricultural assets (0.22). Fertiliser (0.57) and pesticide usage (0.60) were substantially higher, while the CCI value (0.93) clearly reflected a greater degree of commercialisation and market-oriented farming behaviour. Better irrigation availability in Cluster-II enabled farmers to cultivate water-intensive and high-value crops and achieve higher cropping intensity which increased the demand for fertilisers and plant protection chemicals (Pawar and Devendrappa 2022). The presence of fertile deep black and red soils suitable for commercial crops such as sugarcane, chilli and horticultural crops further supported agricultural intensification in these regions. Moreover, the availability of sugar factories and processing units in Cluster-II created assured market opportunities for commercial crops, thereby motivating farmers towards market-oriented production. Baraker *et al.* (2021) study on onion growers in Gadag district observed that better extension participation and market exposure improved marketing behaviour among onion growers. The present study confirms these observations.

Table 1 Results of K-means Clustering Algorithm for the study area

Variables	Cluster-I (n=120)	Cluster-II (n=120)
Age (No. of years)	-0.51	0.52
Gender (male = 1; female = 0)	-0.97	0.98
Education (No. of years)	-0.31	0.32
Family Size (No.)	-0.16	0.23
Agricultural Land (ha)	0.16	-0.14
Non-farm Income (₹/year)	0.06	-0.03
Social Participation (participant = 1; non-participant = 0)	-0.18	0.21
Agricultural Asset Value (₹)	-0.13	0.22
Fertilizer Usage (₹)	-0.18	0.57
Pesticide Usage (₹)	-0.22	0.60
Crop Commercialisation Index (CCI) (%)	-0.82	0.93

Extent of diversification and commercialisation between cluster-I and cluster-II: In the present study, diversification refers to the number of standing crops cultivated on the farm. Table 2 presents the Crop Commercialisation Index (CCI) and Herfindahl-Hirschman Index (HHI), indicating the extent of commercialisation and diversification across

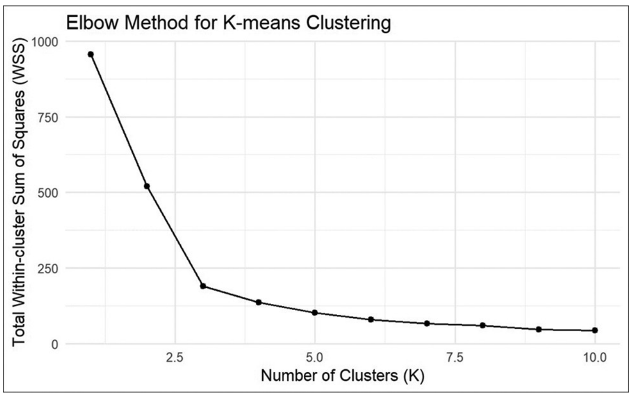

Fig. 1 Graph representing Elbow method for K-means Clustering.

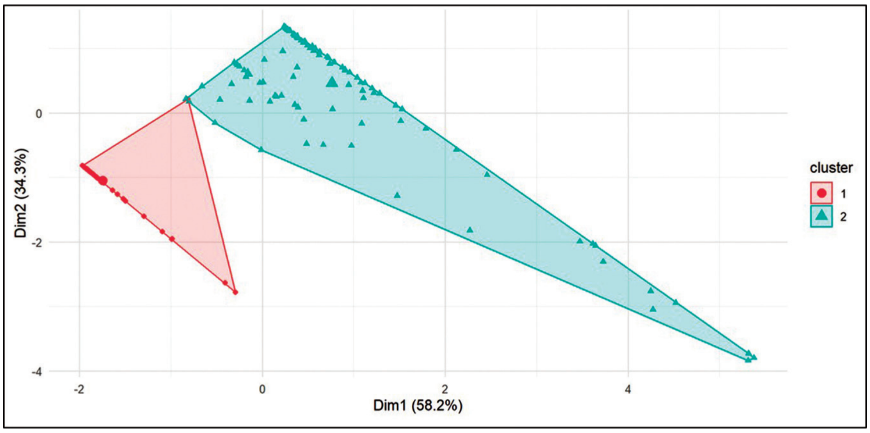

Fig. 2 Graph representing the Cluster Plot resulted from K-means clustering algorithm.

the two clusters. The CCI was comparatively higher in Cluster-II (96.02%) than in Cluster-I (89.54%), reflecting a greater degree of market-oriented farming in Cluster-II under favourable production and market conditions. The HHI value was lower in Cluster-I (0.45) compared to Cluster-II (0.66), indicating relatively higher crop diversification in Cluster-I. Likewise, Singh *et al.* (2022) observed that irrigation intensity and food crop productivity negatively influenced crop diversification, resulting in crop specialisation in Himachal Pradesh. These findings support the present study, where favourable irrigation and market conditions in Cluster-II encouraged concentration towards a few commercial crops such as sugarcane, leading to higher commercialisation with comparatively lower diversification.

However, the findings of Neogi and Ghosh (2022) contradict the present study, as the authors reported that irrigation, fertiliser use, infrastructure development and commercialisation promote diversification towards high-value crops in Indian agriculture. The variation in findings may be due to differences in regional cropping pattern, agro-climatic conditions, market accessibility and the dominance of commercial crops in the study area. Thus, the present study indicates that commercialisation may lead to either diversification or crop concentration depending upon regional production and market conditions.

Mean differences of the factors between diversified and specialised farm households: Table 3 presents the mean differences in socio-economic characteristics between specialised and diversified farm households in the study area. Households were classified based on the HHI.

Table 2 Extent of diversification and commercialisation between Cluster-I and Cluster-II farm household

Variable	Cluster-I (n=120)	Cluster-II (n=120)
Herfindahl-Hirschman Index (HHI)	0.45#	0.66
Crop Commercialisation Index (CCI) (%)	89.54	96.02##

#, ## represents high diversified and high commercialised values, respectively.

The average age of respondents in specialised households was 56.76 years, compared to 53.99 years in diversified households, with a mean difference of 2.77 years. However, the difference was statistically non-significant, indicating that age had limited influence on farm diversification in the study area. Similarly, gender distribution did not showed significant variation between the groups, as all respondents in specialised households were male, while 96% of diversified households were male. This reflects the predominance of male involvement in agricultural decision-making in the study area.

Education showed a statistically significant difference at the 10% level, with diversified households having higher average years of education (6.12 years) than specialised households (4.80 years). Higher educational attainment may have encouraged farmers to adopt diversified farming practices to minimize production and income risks.

The average family size was slightly higher in specialised households (5.62 members) than in diversified households (5.46 members), although the difference was statistically non-significant, suggesting that family size did not substantially influence diversification behaviour in the study area. Likewise, social participation remained almost similar between the two groups, indicating that it was not a major distinguishing factor between specialised and diversified households.

Agricultural asset ownership was significantly higher among specialised households, with an average asset value of ₹10.67 lakh compared to ₹9.66 lakh in diversified households. This may be due to the tendency of specialised households to invest more in specific crops and input-intensive farming activities for improving productivity and returns. The findings are in conformity with Bahinipati and Patnaik (2022), who identified education, demographic characteristics, farm assets and economic factors as important determinants influencing farmers' adaptation, production decisions and farm-level decision-making behaviour in Indian agriculture.

Diversified households possessed relatively larger landholdings (3.43 ha) compared to specialised households (2.49 ha) and the difference was significant at the 5% level. Larger landholdings may provide greater flexibility for cultivating multiple crops and adopting diversified farming systems (Sharma and Shastri 2025). Similar findings were reported by Thejashree and Umesh (2022), who observed significant differences in variables such as asset value and land size among different farm household groups. Overall, the results suggest that education, agricultural assets and landholding size were the major factors influencing diversification and specialisation patterns among farm households in the study area.

Effect of diversification on commercialisation of

Table 3 Mean differences in factors between diversified and specialised farm households area

Variables	Specialised households (HHI>0.5) (n=85)	Diversified households (HHI≤0.5) (n=155)	Mean difference
Age (No. of years)	56.76	53.99	2.77 (1.52)
Gender (male = 1; female = 0)	1.00	0.96	0.04 (0.07)
Education (No. of years)	4.80	6.12	-1.32* (1.92)
Family size (No.)	5.62	5.46	0.16 (1.25)
Social participation (participant = 1; non-participant = 0)	0.19	0.19	-0.00 (-0.17)
Agricultural asset value (₹ in lakh)	10.67	9.66	1.01** (2.38)
Agricultural land (ha)	2.49	3.43	-0.94** (-2.37)

**, * represents Significance at 5% and 10% level. Figures in the parentheses indicates 't' value of corresponding factors, respectively.

agriculture: The results of the Regression Adjustment (RA) model with diversification as the treatment variable are presented in Table 4. The Average Treatment Effect on the Treated (ATET) coefficient was 5.34 with a *z*-value of 6.47 and *p*-value of 0.00, indicating significance at the 1%. The positive and significant ATET value revealed that diversification had a favourable influence on agricultural commercialisation in the study area. The findings indicated that the average per cent of commercialisation would have been 5.34% higher among diversified farm households compared to specialised households. This suggests that farm households cultivating multiple crops were able to generate higher marketed surplus and participate more actively in agricultural markets. The significant *z*-value further confirmed the robustness and reliability of the estimated treatment effect, indicating that diversification substantially enhances commercialisation among farm households.

The Potential Outcome Mean (POM) for diversified households was 58.70 with a *z*-value of 67.90 and *p*-value of 0.00, which was significant at the 1% level. The results indicated that if all the farm households had adopted diversification, the expected average per cent of commercialisation would have been 58.70%. The significant coefficient further revealed that the commercialisation behaviour among diversified households was statistically reliable and not due to random variation. Compared to specialised households, diversified households exhibited relatively higher commercialisation, indicating that diversification played an important role in improving market orientation and farm income in the study area.

The positive effect of diversification on commercialisation may be attributed to increased income opportunities, reduced production risk and improved market participation among diversified households. In the study area, farmers cultivated crops such as sugarcane, cotton, maize, sunflower and soybean, which generated higher marketed surplus and enhanced commercialisation. The results are in agreement with Das and Kumar (2019), who reported that maintaining multiple standing crops improves farm efficiency and commercialisation. Likewise, Ralte and Priscilla (2023) reported that crop diversification towards high-value and commercial crops increases farm income and economic returns per unit area, particularly among small and marginal farmers. The authors further observed that diversification helps strengthen the economic condition of farm households through higher farm output and improved commercialisation. The results are in conformity with the previous study on crop diversification by Thejashree and Umesh (2022). Overall, the findings indicate that diversification contributes not only to higher commercialisation but also to sustainable and economically viable agricultural development.

This study demonstrates that, the relationship between market integration and farm-level diversity is shaped by regional biophysical constraints and resource endowments. While favourable irrigation and processing infrastructure in high-resource zones encourage crop specialisation, regression modelling proves that crop diversification is a powerful catalyst for market integration rather than just a defensive risk-mitigation tool. Crucially, the study highlights that diversification and commercialisation are not contradictory processes, but complementary strategies for achieving economically sustainable agriculture. Transitioning to a heterogeneous crop mix enables smallholders to optimise resource allocation, generate higher marketable surpluses and protect against localised crop failures. To operationalise these findings, targeted policy interventions must be implemented across the two distinct clusters. For Cluster-I, specialised extension programmes should be deployed to build capacity for climate-resilient, low-input crop combinations, tailored specifically to young farmers with low educational baseline metrics. For Cluster-II, structural diversification incentives, such as financial support and credit subsidies must be introduced within heavily irrigated tracts to actively encourage crop rotation

Table 4 Effect of diversification on commercialisation of agriculture (n=240)

Commercialisation	Coefficient	z	*p*>|Z|
Average treatment effect on the treated (ATET) (Diversified vs. Specialised)	5.34	6.47	0.00***
Potential outcome mean (POM) (Diversified)	58.70	67.90	0.00***

*** represents significance at 1% level.

among commercial growers and arrest ongoing natural resource degradation. Finally establishing decentralised market infrastructure and processing facilities in dryland areas is essential to support Cluster-I small holders. While this research provides critical insights, certain limitations offer clear directions for future enquiry. Future studies should integrate institutional credit to capture deeper socio-economic dynamics. Expanding the sample size across diverse climatic regions will improve external validity. Finally, utilizing multi-season panel data will offer critical longitudinal insights into how diversified systems withstand severe, inter-annual climate shocks.

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