Behavioral Dynamics of Sustainable Farming in Mallewadi and Erandoli Villages: Multilevel Analysis of Production Stability, Cost Sensitivity, Technology Adoption, and Market Shock Response

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Abstract: *Existing research in rural agriculture primarily analyzes production, cost, market shocks, and technology adoption in isolation, often within linear and average-based frameworks. Consequently, the nuanced dynamics of farmer decision-making, adaptive capacity and behavioral sensitivity to market shocks remain inadequately understood. This study addresses these gaps by conceptualizing farming decisions in Mallewadi and Erandoli villages as a dynamic, multi-layered, and non-linear decision system. The novelty of this research lies in integrating production stability, cost-response behavior, adoption resistance, market shock sensitivity, and long-term strategic shifts into a unified behavioral framework, rather than treating them independently. Advanced models-Random Forest, Quantile Regression, Multinomial Logistic Regression, Derivative-based GAMs, and XG Boost-capture farmer decisions not merely as average outcomes but as elasticity, regime shifts, and adaptation pathways, a perspective largely absent in existing literature. Findings reveal that Mallewadi exhibits price-driven, shock-sensitive, and unstable decision patterns, whereas Erandoli demonstrates adaptive, shock-absorbing, and long-term oriented strategies. This underscores that market behavior is not solely an economic factor but a decisive determinant of local decision architecture. Uniform agricultural policies may thus be ineffective, emphasizing the need for village-specific, behavior-informed, and risk-responsive interventions. Overall, this research reconceptualizes rural farming from a production system to an adaptive socio-economic decision architecture, providing a benchmark methodological, theoretical, and policy contribution to international agricultural and rural development literature.*

Keywords: Production Stability, Cost Escalation Behavior, Market Shock Sensitivity, Technology Adoption Resistance, Strategic Farming Transitions, Village-Level Analysis, Behavioral Agricultural Economics.

I. INTRODUCTION

Agriculture in developing economies is increasingly shaped by multiple structural pressures rather than only traditional inputs such as land and labor. Rising production uncertainty, increasing input costs, market volatility, and institutional constraints significantly influence farmers' decision-making processes and long-term strategies [9], [10]. In such conditions, understanding agricultural systems requires moving beyond simple indicators such as average yield and focusing on stability and adaptive behavior within farming systems [12]. Rural farmers are exposed to interconnected risks including climate variability, fluctuating market prices, and rising costs of fertilizers, irrigation. These pressures

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affect how farmers allocate resources, adjust production practices, and interact with markets and institutions over time [8], [10]. As a result, agricultural systems must be viewed as dynamic processes shaped by continuous interactions between pressures, responses, and outcomes.

Production stability has therefore emerged as an important indicator of agricultural resilience, reflecting the ability of farming systems to maintain consistent performance despite shocks and uncertainty [12]. At the same time, farmers respond differently to rising production costs and economic pressures, which can be examined using advanced analytical approaches such as quantile-based models that capture heterogeneous behavioral responses [3]. Adoption of sustainable farming practices and modern technologies also varies widely among farmers due to economic risk, limited awareness, and institutional barriers [11], [5]. Market price shocks further influence farmers' production and marketing decisions, often causing nonlinear behavioral responses that require flexible modeling approaches such as generalized additive models [1], [2]. Over time, continuous exposure to these pressures leads to gradual strategic adjustments in farming systems, including diversification, technology adoption decisions, and long-term livelihood planning. Understanding these adaptive processes requires integrating econometric and machine-learning approaches such as multinomial choice models and boosting-based predictive techniques [4], [6], [7].

II. LITERATURE REVIEW

Agricultural Systems and Production Stability

Recent agricultural research has increasingly moved beyond simple yield estimation toward a broader understanding of farmers' decision-making, risk exposure, and production stability. Earlier studies often evaluated agricultural performance using average yield or income levels. However, scholars argue that average output alone does not adequately capture the variability and uncertainty faced by farmers in rural systems. Instead, production stability has emerged as a critical indicator of agricultural resilience and sustainability, reflecting the ability of farming systems to maintain consistent performance under changing environmental and economic conditions [10], [12]. This perspective emphasizes the importance of analyzing farming systems as dynamic socio-economic structures influenced by multiple external pressures.

Machine Learning Approaches in Agricultural Analysis

To better understand complex agricultural dynamics, researchers have increasingly adopted advanced statistical and machine learning techniques. Among these approaches, ensemble models such as Random Forest have gained significant attention due to their ability to capture nonlinear relationships and interactions among variables. Studies using such models have identified production cost, irrigation practices, farm size, and market prices as major determinants of agricultural productivity. The feature importance mechanism of these models helps researchers identify the relative contribution of different factors influencing farming outcomes, thereby providing deeper insights into agricultural decision-making processes [6], [7].

Cost Escalation and Behavioral Responses

Rising production costs represent one of the most critical economic pressures affecting modern agriculture. Increasing expenditures on fertilizers, pesticides, irrigation, and labor place substantial financial burdens on farm households. Researchers have applied Quantile Regression techniques to examine heterogeneous responses to cost escalation across different production levels. Unlike traditional regression methods that estimate average effects, quantile-based approaches allow analysis of variable impacts across the entire distribution of outcomes. Empirical findings suggest that farmers' responses to cost increases vary significantly depending on farm size, access to resources, and risk tolerance, indicating that cost escalation not only affects economic performance but also shapes farmers' behavioral adaptation strategies [3].

Technology Adoption and Resistance in Farming

Adoption of sustainable farming technologies and innovative practices has been widely promoted as a strategy to improve agricultural productivity and environmental sustainability. However, empirical evidence indicates that adoption rates vary widely across regions and communities. Studies using Multinomial Logistic Regression and discrete choice

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frameworks have been used to analyze farmers' technology preferences and adoption barriers. These studies highlight that economic uncertainty, limited awareness, transition costs, and inadequate institutional support frequently discourage farmers from adopting new technologies [4], [5], [11]. Consequently, the concept of technology adoption resistance has gained increasing attention in agricultural research, emphasizing that farmers' reluctance to adopt innovations may represent rational risk-management behavior rather than simple resistance to change.

Market Shocks and Price Sensitivity

Market price volatility also plays a crucial role in shaping agricultural decision-making. Agricultural markets often experience sudden price fluctuations due to supply shocks, policy changes, or global demand shifts. Researchers have applied flexible modeling approaches such as Generalized Additive Models (GAM) to capture nonlinear responses to market price changes. These models allow the identification of smooth relationships and behavioral thresholds in farmers' responses to market shocks. Empirical studies indicate that sensitivity to price fluctuations varies across farming communities depending on market access, institutional support, and economic resilience [1], [2], [8]. Understanding such behavioral responses is essential for evaluating farmers' ability to adapt to unstable market conditions.

Long-Term Strategic Adaptation in Agriculture

Beyond short-term responses to costs and market conditions, farmers often adjust their long-term strategies to manage uncertainty and sustain livelihoods. Increasing climate variability, economic pressures, and market risks have encouraged farmers to diversify their agricultural activities and income sources. Advanced predictive techniques such as gradient boosting algorithms, including XGBoost, have been used to analyze long-term decision patterns and identify key drivers influencing farmers' strategic choices. Research suggests that institutional support, training programs, market access, and local economic conditions significantly influence long-term adaptation strategies in rural agriculture [6], [7].

Integrated Perspective on Agricultural Dynamics

Overall, the existing literature suggests that rural agriculture functions as a complex and adaptive socio-economic system shaped by interconnected pressures and responses. Production stability, cost escalation behavior, technology adoption resistance, market shock sensitivity, and long-term strategic adjustments represent interrelated components of this system. Understanding these dynamics requires integrating econometric and machine learning approaches capable of capturing nonlinear relationships and behavioral heterogeneity. Such integrated analytical frameworks provide valuable insights for improving agricultural resilience and designing effective policies for Sustainable rural development [10],[12].

III. METHODOLOGY

Research Design and Study Area

This study follows a descriptive-analytical research design to examine the dynamic relationships between the pressures faced by farmers, their behavioral responses, and the resulting outcomes. The research adopts the Pathway-of-Pressure Framework, conceptualizing agriculture as a dynamic system where production, economic, and environmental pressures interact with decision-making processes and long-term strategic adaptation.

The study was conducted in selected villages of Sangli District, Maharashtra. This region is representative of mixed cropping systems, including sugarcane, soybean, vegetables, and other commercial crops. The villages were selected due to the following factors

Predominantly agriculture-based economy.
Increasing input costs and production expenses.
Market price fluctuations and economic uncertainty.
Exposure to climatic variability and environmental pressures.

Data Sources and Sampling Method

Primary data were collected directly from farmers through structured questionnaires and interviews. The questionnaire focused on

- Socio-economic characteristics of the farmers.
- Crop selection and management practices.

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- Production costs and input usage.
- Market participation and selling strategies.
- Technology adoption and resistance.
- Perceptions of risk and uncertainty.
  The study used a Stratified Random Sampling technique to ensure representative coverage. Farmers were stratified based on:
- Landholding size.
- Type of crops cultivated.
- Access to irrigation.

Samples were drawn proportionally from each stratum to ensure comprehensive representation of the population.

Variable Structure

1] Pressure Variables

Rising input costs (fertilizers, crop protection, irrigation).
Climatic variability.
Market price fluctuations.
Pest and disease incidence.

2] Response Variables

Changes in cropping patterns.
Input use adjustments.
Adoption or resistance to sustainable practices.
risk management decisions.

3] Outcome Variables

Production stability.
Profitability and losses.
Income variability.
Long-term sustainability.

IV. DATA ANALYSIS TECHNIQUES

1] Descriptive Statistics

Descriptive statistics were applied to summarize the basic features of the dataset. Measures such as mean, standard deviation, minimum, and maximum values were calculated to understand the central tendency and variability of the variables. This step helps provide an initial overview of the dataset before applying advanced analytical models.

Mean Formula: $\bar{X} = \frac{\sum Xi}{n}$

$$(1)$$

$$SD = \sqrt{\frac{\sum (X_i - \bar{X})^2}{n-1}}$$

Where: X_i = individual observation, n = number of observations

2] Graphical Analysis (Normality Assessment)

Graphical techniques were used to examine the distribution pattern of the variables. Histogram plots were generated to visually observe whether the data follow an approximately normal distribution. This graphical assessment helps identify skewness, dispersion, and potential outliers in the dataset.

Normal Distribution Function

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)} \qquad (2)$$

Where: μ = mean of the distribution, σ = standard deviation, x = observed value

3] Correlation Analysis

Correlation analysis was conducted to measure the strength and direction of the relationship between variables. This analysis helps determine whether two variables move together positively or negatively and assists in understanding associations before applying complex statistical models.

Pearson Correlation Coefficient

$$r = \frac{\sum(X_i - X)\,(Y_i - Y)}{\sqrt{(X_i - \bar{X})^2 (Y_i - \bar{Y})^2}} \qquad (3)$$

Where: r = Correlation coefficient, X_i, Y_i = Observed values, $X_{i,}$ Y= Mean values

4] Model Evaluation Metrics

To evaluate the performance of classification models, several evaluation metrics were used. These measures help determine the accuracy and reliability of model predictions.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (4)$$

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (5)$$

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (6)$$

(7)

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where: TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative

V. MACHINE LEARNING MODELS

To examine different aspects of agricultural decision-making and production dynamics, several machine learning and econometric models were applied. These models help analyze complex relationships between variables and improve predictive accuracy compared with traditional statistical methods.

5.1] Random Forest Model (Production Stability)

Random Forest is an ensemble machine learning algorithm that constructs multiple decision trees and combines their predictions to improve accuracy and reduce overfitting. This method is useful for identifying important factors influencing agricultural production.

Formula

$$\hat{\mathrm{Y}} = \frac{1}{\mathrm{T}} \sum_{t=1}^{\mathrm{T}} \mathrm{h}_t(\mathrm{X}) \qquad (8)$$

Where: T = Number of trees in the forest, $h_t(X)$ = Prediction from the t^{th} decision tree, $\hat{Y}$= Final Prediction.

5.2] Linear Quantile Regression (Cost Escalation Behaviour)

Linear Quantile Regression is used to examine how explanatory variables influence different points of the conditional distribution of the dependent variable. This approach helps analyze heterogeneous effects across various quantiles.

Formula

$$Q_y\ (\tau|X)\ = X\ \beta_\tau \qquad (9)$$

Where:

$Q_y\ (\tau|X)$ = conditional τ-th quantile of the response variable y given predictors X

X = vector of independent variables

β_τ = coefficient vector corresponding to the τ-th Quantile

$\tau\ \varepsilon\ (0, 1)$ = quantile of interest

5.3] Multinomial Logistic Regression (Technology Adoption)

Multinomial Logistic Regression is applied when the dependent variable contains more than two categories. It is used to analyze farmers' choice behavior regarding different agricultural practices.

Formula

$$\text{Log}\ \frac{P(Y = K\mid X)}{P(Y = k\mid X)} = \beta_{0k} + \beta_{1k}X_1 + \beta_{2k}X_2 + \ldots\ldots\ldots + \beta_{pk}X_p \qquad \text{for each k = 1, 2…..k – 1.} \quad (10)$$

Where:

$P(Y = K \mid X)$ = probability of outcome k given predictors.

$P(Y = k \mid X)$ = probability of **baseline/reference class.**

β_{0k} = intercept for class k.

β_{ik} = coefficient for predictor X_i for class k.

5.4] Generalized Additive Model (Market Shock Sensitivity)

The Generalized Additive Model (GAM) allows flexible modeling of nonlinear relationships between variables by using smooth functions.

Formula (11)

$$Y_i = \beta_0 + f_1X_{1i} + f_2X_{2i} + \ldots\ldots\ldots + f_kX_{ki} + \varepsilon_i$$

Where:

Y_i = represents the dependent variable.

β_0 = is the intercept term.

$X_{1i}, X_{2i}, \ldots\ldots\ldots\ X_{ki}$ = are the independent variables.

$f_1()$, $f_2()$, $f_k()$ = are smooth, non-linear functions estimated from the data.

ε_i = denotes the random error term.

5.5] XG Boost Model (Long-Term Strategy)

XG Boost is a gradient boosting algorithm that sequentially builds decision trees to improve predictive accuracy.

Formula:

$$\hat{Y}_i = \sum_{k=1}^{K} f_k(x_i) \qquad f_k\ \varepsilon\ \mathcal{F} \qquad (12)$$

Where: x_i = Input features, $\mathcal{F}$ = Set of all possible regression trees.

VI. GRAPHICAL ANALYSIS

In the present study, graphical representation is employed as a systematic exploratory tool to understand the underlying structure, distributional characteristics, and interrelationships within the dataset before any form of advanced statistical interpretation. The purpose of this visual exploration is not prediction, but to critically examine production stability, cost behavior, and market-linked variations in agricultural output.

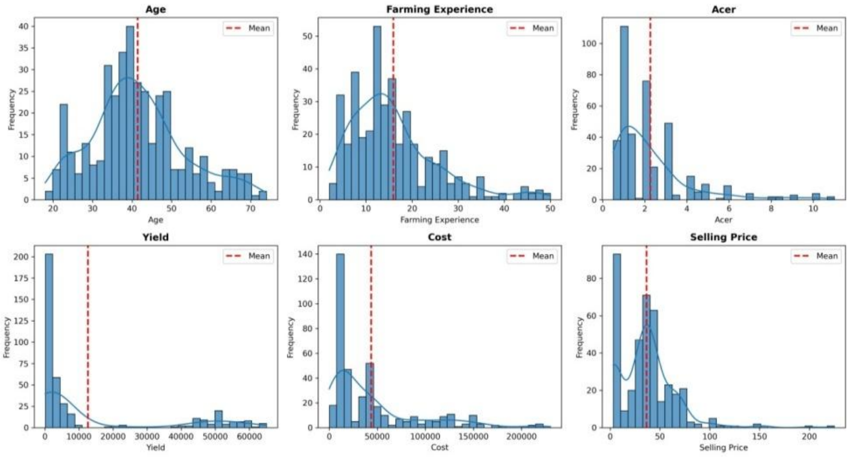

Fig.1 Histogram

Fig.1 analysis was conducted for key continuous variables including Age, Farming Experience, Acre age, Yield, Cost, and Selling Price. Age shows a normal distribution, supporting the use of parametric practices for demographic analysis. In contrast, Farming Experience, Acre age, Yield, Cost, and Selling Price are non-normal, reflecting heterogeneity among smallholder farmers. Right-skewed patterns in Farming Experience and Acre age indicate that most farmers have moderate experience and operate small plots, while a few are highly experienced or manage larger holdings. Yield displays multiple peaks, highlighting variability due to management practices, and environmental factors. Non-normal Cost and Selling Price distributions indicate variations in input expenditure and market returns, relevant for analyzing village-wise cost behavior and market response. Overall, these patterns provide a clear, objective-aligned understanding of production stability, cost behavior, and market-influenced agronomics outcomes.

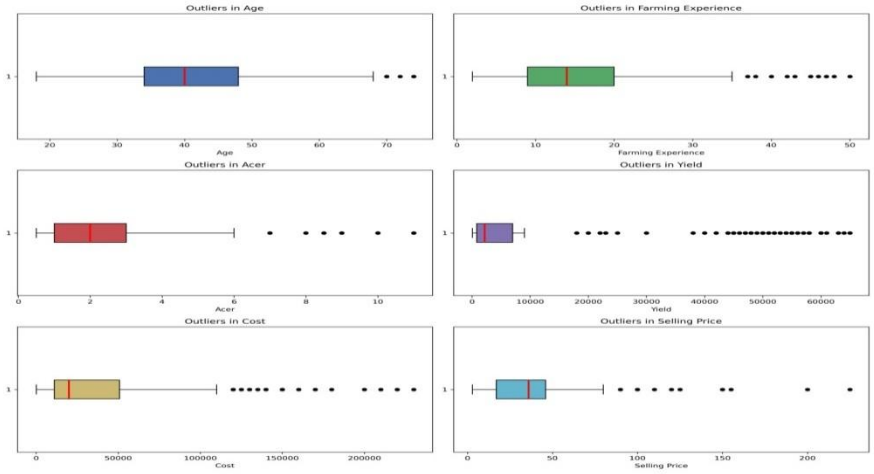

Fig.2 Box Plot

Fig.2 analysis reveals the presence of outliers across key variables including Yield, Cost, Selling Price, Acreage, and Farming Experience. These outliers are not treated merely as statistical anomalies but represent real-world agricultural variability arising from factors such as sudden cost escalation, market price volatility, climatic stress, and differences in farm management. Outliers observed in Cost and Selling Price is particularly relevant for understanding village-wise cost response behavior and market sensitivity. Yield-related outliers indicate uneven production stability among farmers, while those in Acreage and Experience reflect structural heterogeneity within the farming system. Overall, the identification of outliers supports the use of robust and non-parametric analytical approaches and strengthens objective-aligned interpretation.

Fig.3 shows that yield stability is not solely determined by crop biology but is tightly linked to local farm management and resource allocation strategies. The strong positive correlation of sugarcane reflects long-term experience and irrigation-driven management, while crop rotation shows a negative correlation when applied (Yes) and a positive correlation when not applied (No), indicating that diversification does not always enhance yield. In Erandoli, the negative correlation between selling price and yield highlights that production decisions are often independent of market fluctuations. Sorghum exhibits a mild negative correlation in both villages, emphasizing its secondary role in resource allocation. Collectively, these results demonstrate that yield stability emerges from the internal coherence of village specific agricultural systems, rather than from individual factors alone.

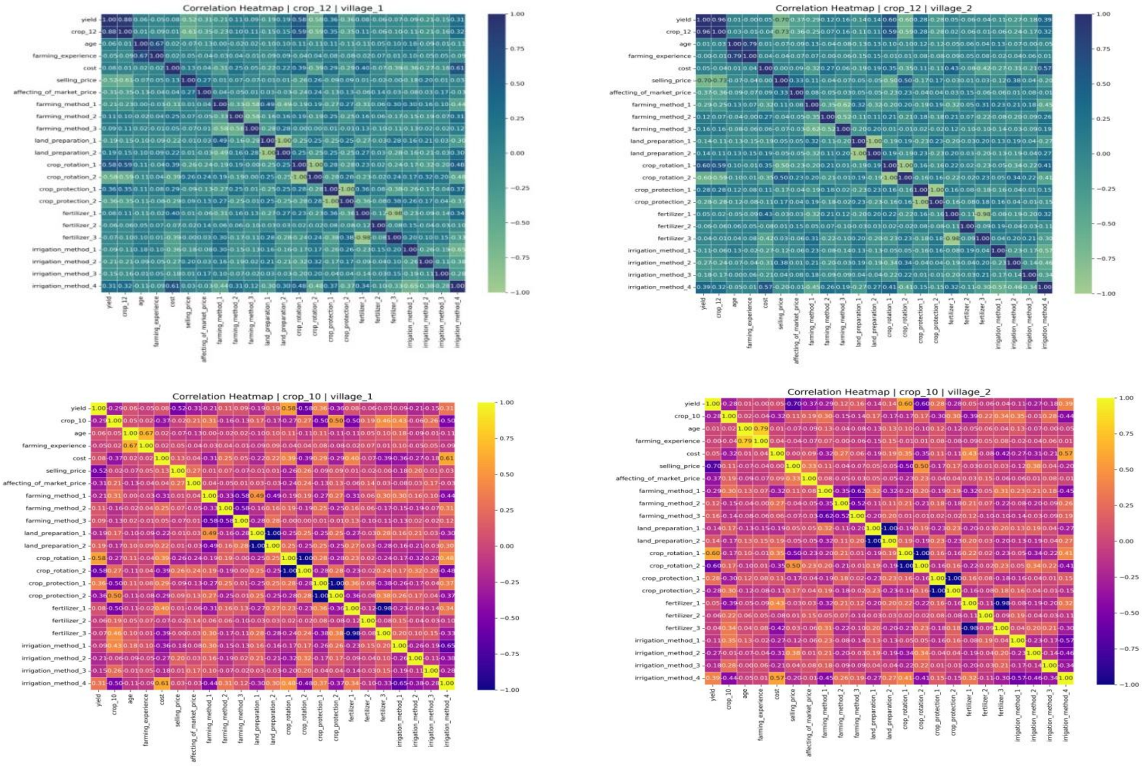

Fig.3 village-wise correlation heat map

VII. STATISTICAL ANALYSIS

Production Stability

In Mallewadi and Erandoli villages, production stability is not merely an indicator of average yield but reflects a complex, non-linear, village-specific pattern arising from the interactions of management practices, irrigation, market conditions, and resource availability. In this context, the Random Forest model is particularly suitable because it can effectively capture village-wise heterogeneity, interactions among multiple continuous and categorical variables, and complex system dynamics. The model not only provides accurate yield predictions but also identifies key drivers through variable importance, highlighting the factors that most influence production stability. Consequently, Random Forest enables a deeper understanding of the system-level patterns and underlying dynamics of village-wise production, offering insights beyond what traditional regression or simple statistical methods can provide. This approach delivers both predictive accuracy and theoretical insight, linking agricultural management strategies directly to observed stability patterns.

Model Performance

TABLE I

Village	R^2 score
Mallewadi	0.93
Erandoli	0.94

Fig.4 Village-Wise Feature Drivers Of Production Stability

Fig.4 feature importance analysis reveals that production stability in both Mallewadi and Erandoli villages is driven primarily by cost control rather than by crop choice or farming diversity. The negligible influence of mixed farming in Mallewadi indicates that diversification does not function as a stabilizing mechanism; instead, stability emerges from resource concentration and consistent management strategies. Similarly, the minimal contribution of maize in Erandoli suggests that certain crops play a peripheral role and do not influence core production decisions. The dominance of cost as a predictor across both villages highlights highlights that yield stability is anchored in economic discipline and strategic allocation of inputs rather than in the number of crops or methods adopted. Collectively, these findings reframe production stability as a system-level, cost-anchored outcome, shaped by village-specific decision hierarchies and long-term management coherence.

TABLE II

Village	Mean	Median	STD	Min.	Max.
Mallewadi	0.0950	0.2573	1.3133	- 3.7407	4.7036
Erandoli	- 0.0950	0.1734	1.1860	-4.3290	2.2125

The above data is pictured in the next graph.

Fig.5 indices reveal distinct structural patterns of stability and risk between Mallewadi and Erandoli villages. In Mallewadi, a positive mean and relatively high median indicate a central tendency toward higher production stability; however, the large standard deviation and wide min–max range suggest that this stability is heterogeneous and highly sensitive to extreme fluctuations, reflecting a “high-return high-risk” system. In contrast, Erandoli exhibits a slightly negative mean but a positive median, implying that extreme negative deviations have suppressed the average, while the lower standard deviation indicates a more consistent, controlled, and predictable production environment, characteristic of a “moderate-return controlled-risk” system. Collectively, these results demonstrate that village-specific management practices, crop selection, and cost structures exert decisive influence on production stability, highlighting how local agronomic and economic strategies shape system-level resilience.

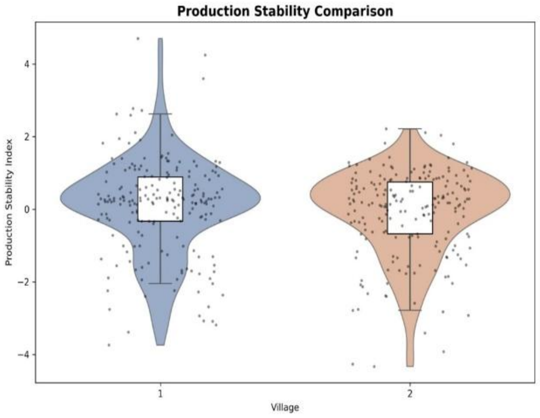

Fig.5 Village-wise Production Stability Comparison

Cost Escalation Behaviour

Understanding farmers' behavioral responses to rising production costs is critical for agricultural economics and policy planning. However, measuring only the average response cannot capture the profound heterogeneity inherent in farming behavior. Quantile Regression provides a robust solution, as it enables detailed analysis of farmers' responses across different cost-sensitive quintiles - low, medium, and high. In the villages of Mallewadi and Erandoli, this approach allows village-specific examination of how economic conditions, crop choices, and management practices influence cost escalation responses. Quantile Regression goes beyond mean effects to reveal the behaviors of both extreme cost-sensitive and cost-resilient farmers, offering nuanced insights into system dynamics. Consequently, this method supports the design of targeted interventions, financial assistance, and resource allocation strategies tailored to each village's needs. From this perspective, the study provides a multidimensional understanding of farmers' cost sensitivity, enhancing rural policy frameworks.

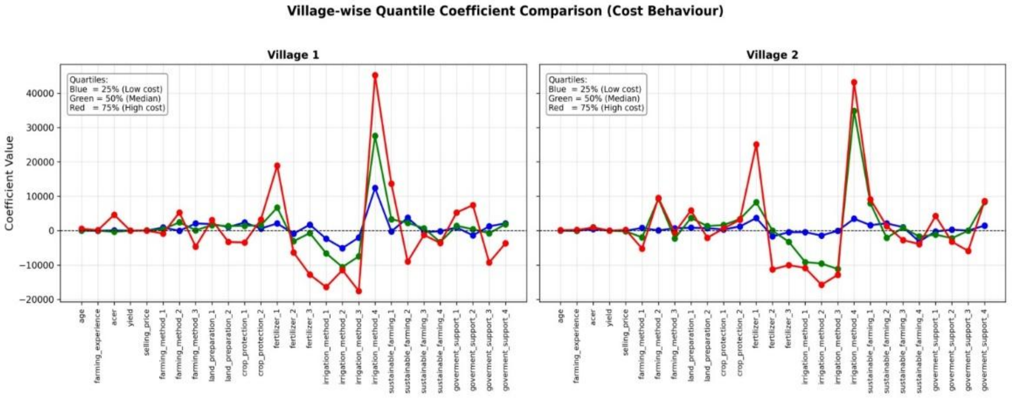

Fig.6 Village-wise Cost behavioral

Fig.6 results demonstrate that production cost escalation is not a uniform economic response but a stratified, risk-conditioned behavioral process that varies fundamentally across cost levels. In Mallewadi, the rising dominance of rainfall at higher cost Quantiles reflects not simple input dependence but risk-driven commitment escalation, where farmers intensify investment under climatic uncertainty, while the negative effects of flood conditions and sprinkler irrigation indicate deliberate cost-containment behavior at the upper tail of the cost distribution. In Erandoli, the strengthening impact of rainfall across middle and upper Quantiles signals production intensification under climate exposure, whereas the pronounced negative association of drip and sprinkler irrigation reveals the role of technology not as a productivity input but as an institutional cost-buffer that dampens expenditure volatility. Collectively, these findings establish that cost escalation in agriculture is neither linear nor average-driven; rather, it is governed by Quantile-specific, village-embedded, and climate-technology mediated economic regimes, challenging conventional mean-based cost analyses and advancing a behavioral re-interpretation of agricultural cost dynamics.

Technology Adoption

Resistance to the adoption of sustainable and organic farming practices is not a simple binary decision between acceptance and rejection; rather, it represents a strategic behavioral equilibrium shaped by farmers' efforts to manage production risk and economic uncertainty. Farmers do not uniformly oppose new technologies; instead, they position themselves across multiple resistance levels, influenced by cost volatility, input dependency, irrigation infrastructure, institutional trust, and experiential uncertainty. Because this decision structure is inherently non-binary, the present study employs a multinomial logistic regression framework to conceptualize technology adoption resistance as a multilevel behavioral outcome rather than a yes–no choice. The contrasting resistance patterns observed between Mallewadi and Erandoli-two villages embedded in distinct agro-economic environments-demonstrate that resistance to sustainable farming technologies is not an individual anomaly but a location-specific economic rationality. By moving beyond mean-based adoption models, this approach reveals how structural constraints and perceived risk jointly shape differentiated resistance pathways, thereby exposing a critical limitation in conventional technology adoption literature.

Model Performance

TABLE III

Village	R^2 score
Mallewadi	0.46
Erandoli	0.55

TABLE VI

	precision	Recall	F1-score	Support
Water Management	0.47	0.68	0.56	25
Soil Improvement	0.67	0.47	0.55	17
Orga. Fert & Pest	0.25	0.30	0.27	10
All Classes	0	0	0	8
Accuracy	-	-	0.47	60
Macro avg.	0.35	0.36	0.35	60
Weighted avg.	0.43	0.47	0.43	60

Table.VI the factors likely to be most crucial for environmentally sustainable farming in the future, the confusion matrix and classification report provide clear insights into farmers' decision-making structures. Water Management exhibits relatively high recall (0.68) and a stable F1-score (0.56), indicating that farmers primarily associate sustainability with factors linked to immediate production stability, climate risk, and uncertainty management. Soil Health Improvement shows higher precision (0.67) but lower recall (0.47), suggesting that although its long-term importance is recognized, it is not consistently translated into actual decision-making. Organic fertilizers and pesticides record very low precision, recall, and F1-score (0.27), reflecting adoption hesitancy driven by financial risk and uncertainty regarding outcomes. Notably, the "All of the above" category shows zero classification accuracy, revealing the absence of a systems-level perspective among farmers, who tend to evaluate sustainability components in isolation. Overall, the results highlight fragmented adoption behavior, underscoring the need for integrated policy interventions, coordinated extension strategies, and farmer-centric capacity building to promote holistic sustainability adoption.

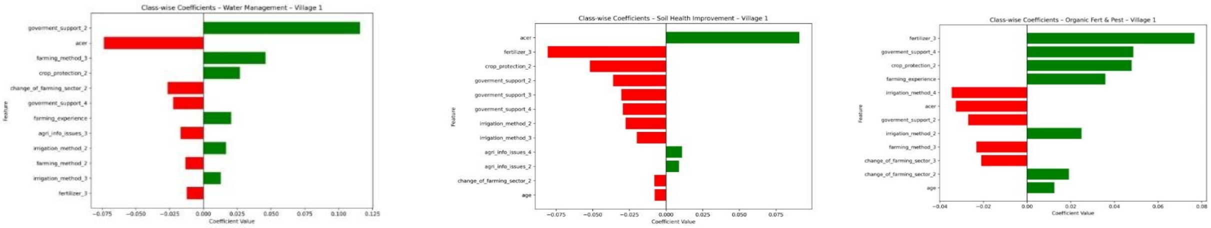

Fig.7 Feature and Class-Wise Coefficient Mallewadi

Fig.7 indicates that farmers' decision-making is shaped by distinct drivers across sustainability dimensions. In Mallewadi, Water Management decisions are most strongly influenced by subsidies (0.115), highlighting the central role of policy incentives, whereas the negative effect of land size (Acre: −0.04) suggests reduced marginal investment by larger farmers. For Soil Health Improvement, a positive association with Acre (0.078) and a negative association with Organic inputs (−0.078) imply that land scale supports soil interventions, while input intensity alone does not ensure yield gains. In the Organic Fertilizer and Pesticide class, the positive coefficient for Organic inputs (0.07) and negative effects of Drip irrigation and Acre (−0.03) reflect interdependencies between input choice, irrigation strategy, and farm scale. Within the "All of the above" class, Training Programs show a positive influence (0.05), whereas Farming Experience and Subsidies exert negative effects (−0.057), indicating structural and behavioral barriers to integrated adoption

TABLE V

	precision	Recall	F1-score	Support
Water Management	0.53	0.88	0.66	24
Soil Improvement	0.85	0.58	0.69	19
Orga.Fert & Pest	0.14	0.10	0.12	10
All Classes	0	0	0	7
Accuracy	-	-	0.55	60
Macro avg.	0.38	0.39	0.37	60
Weighted avg.	0.50	0.55	0.50	60

Table.V outcomes for Erandoli village indicate a distinct ordering in farmers' sustainability perceptions. Strong diagonal accuracy for *Water Management* (87.5%) and moderate accuracy for *Soil Health Improvement* (57.9%), supported by high recall (0.88) and precision (0.85), confirm that farmers consistently prioritize practices linked to immediate resource security. Conversely, the *Organic Fertilizers and Pesticides* class shows limited predictive strength, while the *All of the Above* category records zero precision, recall, and F1-score, reflecting weak conceptual integration of multiple sustainability elements. The overall accuracy of 55%, coupled with lower macro-average than weighted-average scores, suggests uneven class recognition driven by selective preference rather than balanced understanding. These results reveal that sustainability adoption in Erandoli is fragmented and sequential, favoring tangible short-term benefits over holistic strategies. Therefore, effective interventions must emphasize cognitive integration of sustainability components through focused extension efforts and context-specific awareness initiatives rather than isolated technical promotion.

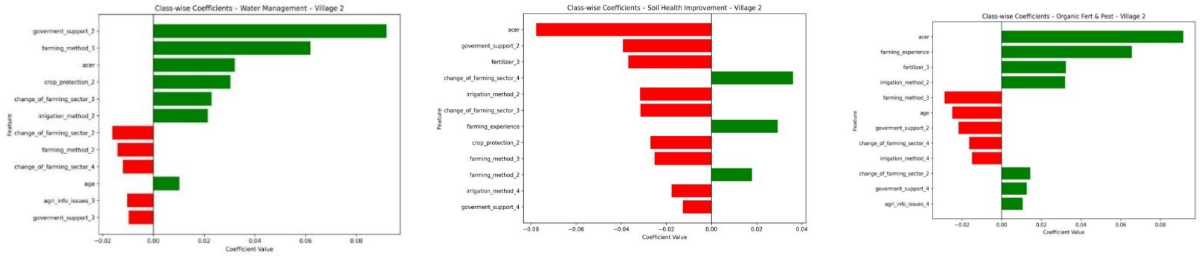

Fig.8 Feature and Class-Wise Coefficient Erandoli

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Fig.8 model indicate that technology adoption in Erandoli village is selective, incentive-driven, and structurally fragmented rather than holistic. Across all classes, positive coefficients are consistently associated with variables such as subsidies, drip irrigation, and cultivated area, suggesting that farmers respond more strongly to direct economic incentives and scale-related efficiency gains than to broader sustainability considerations. This implies that environmentally sustainable practices are primarily adopted when they reduce immediate financial risk rather than when they offer long-term ecological benefits. Conversely, negative coefficients linked to farming experience, agro-processing involvement, and mixed farming methods reveal a persistent resistance rooted in entrenched production routines. More experienced farmers appear less inclined toward integrated sustainability frameworks, indicating that accumulated experience may reinforce conventional practices instead of facilitating innovation. The weak and inconsistent coefficients observed for the "All of the above" category further confirm that farmers tend to adopt individual components of sustainable farming independently rather than as a comprehensive technological package. Overall, the findings demonstrate that sustainable technology adoption in Erandoli is governed by cost-benefit rationality and risk aversion, not by integrated environmental awareness. This highlights a critical policy gap: without coordinated incentives and targeted behavioral interventions, sustainability transitions are likely to remain partial, segmented, and technologically incomplete.

Market Shock Sensitivity

Agricultural markets are highly volatile, and sudden price fluctuations exert a significant influence on farmers' production and selling decisions. Farmers' responses to market shocks are rarely linear, as minor price changes may trigger limited reactions, while sharp price movements can cause substantial behavioral shifts. Conventional linear models often fail to capture these complex and asymmetric response patterns. In this context, the Generalized Additive Model (GAM) provides a flexible analytical framework by allowing non-linear and smooth relationships between market prices and decision variables. GAM effectively identifies threshold effects and varying degrees of sensitivity across different price ranges. In the present study, GAM is applied to assess market shock sensitivity among farmers in Mallewadi and Erandoli villages. The model captures village-specific behavioral responses to sudden price changes and their implications for production stability and marketing choices. This approach offers deeper insights into price-risk transmission mechanisms and supports the design of targeted market stabilization and risk-management policies.

Model Performance

TABLE VI

Village	R^2 score
Mallewadi	0.89
Erandoli	0.86

Fig.9, this study captures both price effects and behavioral sensitivity to market shocks. Mallewadi shows high initial responsiveness, but sensitivity declines sharply as shocks intensify, indicating unstable decision-making and weak shock-absorption capacity. Erandoli, in contrast, exhibits controlled price responses with near-zero derivatives, reflecting stable, adaptive, and resilience-driven behavior. The contrasting sensitivity paths reveal a clear behavioral regime shift, confirming that farmer responses to market shocks are structurally village-specific. These results demonstrate that uniform policy interventions are ineffective and highlight the methodological strength of derivative-based GAM in quantifying dynamic behavioral responses in rural markets.

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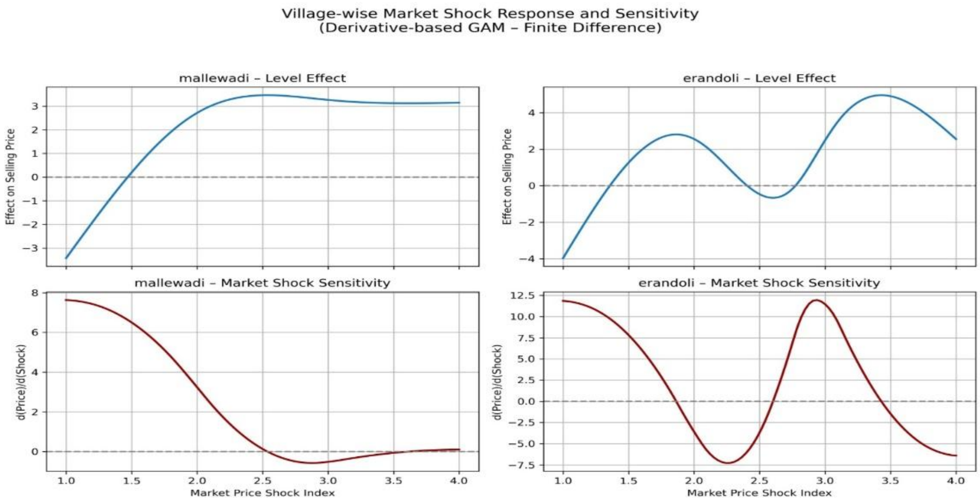

Fig.9 Village-wise Market Shock Response and Sensitivity

Long-Term Strategy

The long-term farming strategies of farmers are influenced by a combination of economic, environmental, and market factors. Village-wise contributions in Mallewadi and Erandoli were quantified using XG Boost-based predictive modeling. In Mallewadi, high costs (High Cost Z) and the effect of mixed farming methods are key drivers of strategic shifts. In Erandoli, high costs and maize-related effects play the most significant role. The village-wise analysis shows that farmers' strategies are primarily focused on production stability and risk mitigation. In Mallewadi, cost optimization and mixed method efficiency are of utmost importance. In Erandoli, crop selection and expenditure control are the primary determinants. Strategic shifts in both villages are dependent on local resources, market fluctuations, and farmer experience. Feature importance and predictive insights from XG Boost allow for targeted interventions and localized advisory. This study provides a village-specific, evidence-based, and scalable framework for guiding sustainable farming strategies.

Model Performance

TABLE VI

Village	R^2 score
Mallewadi	0.56
Erandoli	0.61

Table.VII In Mallewadi, farmers prioritize Animal Husbandry (precision 0.62, recall 0.67) and Agro Processing (precision 0.59, recall 0.56), while adoption of Organic Farming and Technology-based Farming remains limited, indicating constrained strategic diversity. This reflects economic risk aversion, lower technological engagement, and reliance on traditional practices, resulting in largely component-specific, price-driven long-term strategies. Mallewadi is price-driven and resource-constrained, requiring strategic interventions, training programs, and economic support.

TABLE VII

	precision	Recall	F1-score	Support
Animal Husbandry	0.62	0.67	0.65	30
Organic Farming	0.25	0.25	0.25	4
Agro Processing	0.59	0.56	0.57	18

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Technology	0.43	0.38	0.40	8
Accuracy	-	-	0.57	60
Macro avg.	0.47	0.46	0.47	60
Weighted avg.	0.56	0.57	0.56	60

Table.VIII In Erandoli, Animal Husbandry (precision 0.65, recall 0.77) and Technology-based Farming (precision 0.57, recall 0.57) are more widely adopted, while Organic Farming shows negligible adoption, highlighting adoption hesitation and knowledge gaps. Moderate adoption in Agro Processing (precision 0.62, recall 0.54) indicates selective uptake of modern practices. Overall accuracies (Mallewadi 56.7%, Erandoli 61.7%) and weighted averages (0.56, 0.60) confirm the model reliably represents farmers' decision-making, while adoption asymmetry remains evident. Erandoli is more technology-aware and adaptive, with balanced market-responsive behavior.

TABLE VIII

	precision	**Recall**	**F1-score**	**Support**
Animal Husbandry	0.65	0.77	0.70	26
Organic Farming	0.00	0.00	0.00	3
Agro Processing	0.62	0.54	0.58	24
Technology	0.57	0.57	0.57	7
Accuracy	-	-	0.62	60
Macro avg.	0.46	0.47	0.46	60
Weighted avg.	0.59	0.62	0.60	60

Fig.10 analysis reveals the most influential factors shaping farmers' long-term strategic decisions. In Mallewadi, Training Programs emerge as the most impactful (7.12%), highlighting the critical role of technical knowledge and capacity building in farmer decision-making. This is followed by the Agricultural Department (6.67%), emphasizing the importance of policy guidance and government support, while Sugarcane (2.92%) shows the least influence, indicating limited strategic reliance on certain crops

In Erandoli, Local Market (7.20%) dominates, reflecting the strong influence of market availability, demand, and price signals on farmers' strategies. The Agricultural Department (6.16%) remains significant, whereas Wheat (3.43%) exerts minimal impact. These village-wise differences indicate that Mallewadi farmers depend more on training and institutional support, whereas Erandoli farmers prioritize market-driven factors. This comparative insight underscores the need for localized policy interventions, targeted training programs, and market-oriented strategies to enhance long-term strategic decision-making among farmers in different villages.

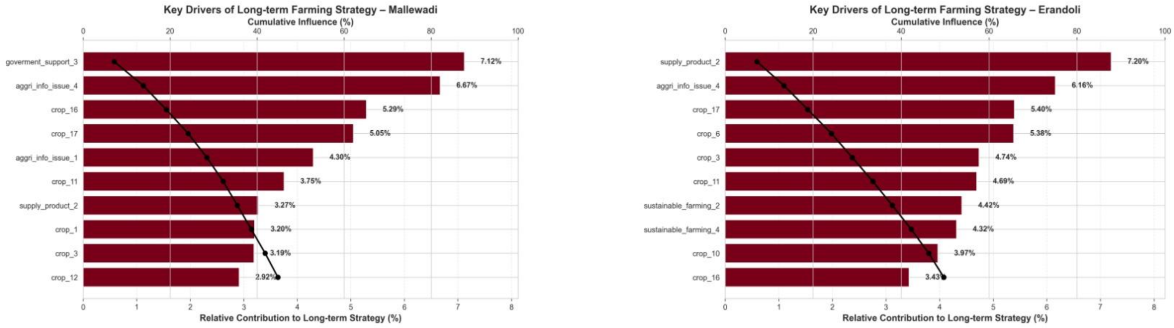

Fig.10 Village-wise Feature Importance

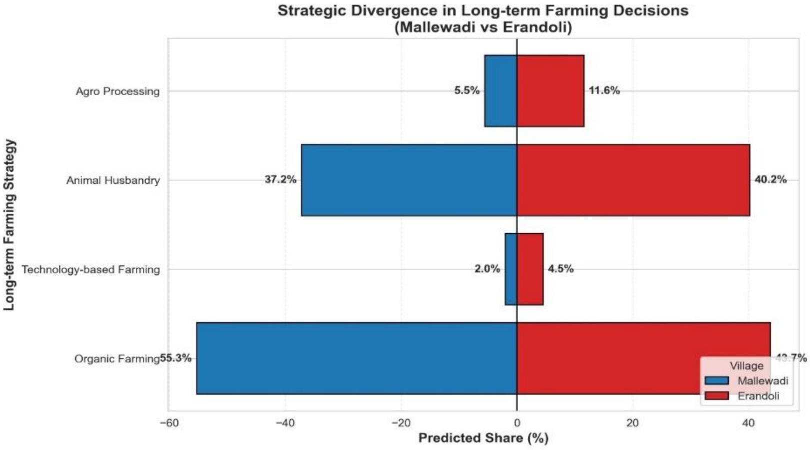

Fig.11 Village-wise Predicted Strategy

Fig.11 analysis highlights the long-term farming priorities of farmers in Mallewadi and Erandoli villages. In Mallewadi, Organic Farming (55.3%) emerges as the most dominant strategy, reflecting strong adoption of sustainable agricultural practices, while Animal Husbandry (37.2%) remains a key complementary strategy, supporting both nutrition and economic stability. Agro Processing (5.5%) and Technology-based Farming (2%) exhibit minimal influence, indicating limited utilization of local processing capabilities and modern technology. In Erandoli, Animal Husbandry (40.2%) and Organic Farming (48.7%) are the primary strategic choices, revealing a balanced approach that integrates market sensitivity with sustainable practices. Agro Processing (11.6%) and Technology-based Farming (4.5%) show moderate effects, suggesting a slightly greater role for local market engagement and adoption of technological interventions.

These results indicate that Mallewadi is more reliant on sustainable practices, whereas Erandoli exhibits a balanced strategy emphasizing both market-oriented and sustainable approaches. The findings underscore the critical role of local market development, targeted training programs, and policy interventions in shaping effective long-term farming strategies.

VIII. CONCLUSION

This study conclusively demonstrates that farmers’ decision-making in Mallewadi and Erandoli is not driven solely by production outcomes or income considerations, but functions as a risk-sensitive, institutionally influenced, and long-term adaptive system. The findings clearly show that traditional mean-based analyses are insufficient to capture the true dynamics of rural agricultural behavior. The derivative-based GAM analysis reveals that market price shocks do not merely alter price levels; they induce behavioral regime shifts in farmers’ responses. Mallewadi exhibits high sensitivity with low shock-absorption capacity, resulting in unstable and nonlinear decision responses under increasing market stress. In contrast, Erandoli demonstrates a controlled and adaptive response structure, indicating stronger resilience and decision stability. Results from the XG Boost-based long-term strategy analysis further indicate that future farming strategies are shaped less by immediate technological availability and more by training exposure, institutional support, and local market structure. This confirms that agricultural transformation in these villages is not purely technological but represents a deeper institutional and behavioral transition. Taken together, the study conceptualizes rural agriculture as a complex adaptive socio-economic system, highlighting the limitations of uniform policy interventions. By integrating advanced econometric modeling with machine-learning techniques, this research offers a novel methodological framework, robust behavioral interpretation, and policy-relevant insights, making a substantive contribution to international agricultural economics and rural development literature.

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