World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(RESEARCH ARTICLE)

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FARMER TRAINING AND ADOPTION OF CLIMATE-SMART AGRICULTURAL INNOVATIONS AMONG SMALL-SCALE FARMERS IN MACHAKOS COUNTY, KENYA

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World Journal of Advanced Research and Reviews, 2026, 31(03), 068–075

Publica Publication history: Received on 25 July 2026; revised on 31 August 2026; accepted on 02 September 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.31.3.2265

ABSTRACT

Climate-smart agricultural innovations can strengthen farm resilience, but their adoption depends partly on whether farmers acquire the knowledge and practical capability required for implementation. This study examined the relationship between farmer training and the adoption of climate-smart agricultural innovations among small-scale farmers in Kalama Ward, Machakos County, Kenya. A descriptive cross-sectional research design was used. From a beneficiary population of 600 farmers, 240 were sampled through multistage sampling, and 221 returned usable questionnaires, giving a response rate of 92.1%. Eight purposively selected key informants were also interviewed. Quantitative data were analyzed using descriptive statistics, Pearson correlation, and multiple linear regression, while qualitative evidence was analyzed thematically and used to support interpretation. Farmer training received a favorable composite rating ($M = 4.03$, $SD = 0.86$). Training had a strong positive correlation with adoption ($r = 0.741$, $p < 0.01$) and made the largest unique contribution in the four-predictor regression model ($\beta = 0.378$, $p < 0.001$). Practical demonstrations, improved understanding, extension guidance, and opportunities for peer learning emerged as important training mechanisms. However, training frequency and post-training support received comparatively lower ratings. The study concludes that structured, practical, and continuous farmer training is strongly associated with the uptake and continued application of climate-smart agricultural innovations. Agricultural agencies and project implementers should combine demonstrations, farmer field schools, peer learning, and sustained extension follow-up to strengthen adoption.

Keywords: Climate-smart agriculture; Farmer training; Innovation adoption; Small-scale farmers; Project management; Machakos County

1 INTRODUCTION

Agricultural production in dry areas is increasingly affected by irregular rainfall, recurrent drought, water stress, and declining soil quality. These pressures are particularly detrimental for small-scale farmers whose livelihoods depend on climate-sensitive production systems and whose capacity to absorb losses is limited. Climate-smart agriculture offers a coordinated approach for protecting and improving productivity, strengthening resilience, and reducing emissions where practicable (Food and Agriculture Organization of the United Nations [FAO], 2023; Intergovernmental Panel on

Climate Change [IPCC], 2022). Commonly promoted innovations include drought-tolerant crop varieties, water harvesting, conservation agriculture, agroforestry, and improved soil-management practices.

The availability of an innovation does not by itself ensure adoption. Farmers must understand how a practice works, how it fits local farming conditions, and how it can be applied with available resources. Training can reduce uncertainty, build practical competence, and strengthen confidence in testing and continuing an unfamiliar practice. Demonstration plots, farmer field schools, extension visits, peer learning, and follow-up assistance can therefore influence whether project beneficiaries move from awareness to sustained application (FAO, 2023; Mwongera et al., 2017).

In Kenya, climate-smart agricultural programmes operate within diverse ecological and institutional conditions. Machakos County is largely semi-arid, and farming households regularly experience unreliable rainfall and water stress. Government agencies, non-governmental organizations, and development partners have promoted climate-smart innovations within the county. Nevertheless, uptake and continued use remain uneven. Existing studies have often explained adoption through household characteristics, access to information, finance, inputs, and extension services. Less attention has been given to training as a project-management practice and to the specific mechanisms through which training supports adoption (Mugambi et al., 2021; Njuguna et al., 2022).

This article isolates farmer training from the broader thesis model and examines its relationship with the adoption of climate-smart agricultural innovations among small-scale farmers in Kalama Ward. The evidence addresses a practical implementation question: whether farmer training which is adequate, relevant, practical, continuous, and supported by extension follow-up is associated with stronger adoption.

2 LITERATURE REVIEW AND THEORETICAL FOUNDATION

2.1 Farmer Training and Agricultural Innovation Adoption

Training is a capability-development function within agricultural projects. It translates technical information into knowledge and skills that beneficiaries can apply. Effective training is not limited to classroom instruction. It includes practical demonstrations, opportunities to practice, locally relevant examples, understandable learning materials, peer exchange, and follow-up support. These features are especially important where innovations require changes in routine farm operations or involve unfamiliar timing, inputs, and risk-management practices.

Evidence from sub-Saharan Africa generally links extension contact and training with greater use of agricultural technologies. Training can improve awareness of an innovation's expected benefits, reduce perceived complexity, and provide farmers with opportunities to observe results before committing resources (Wossen et al., 2022). Demonstration-based approaches can also strengthen confidence because farmers see how a method performs under conditions similar to their own. Mwongera et al. (2017) emphasized participatory appraisal and local prioritization when scaling climate-smart agriculture, while Muriithi et al. (2021) drew attention to the role of information and institutional support in eastern Kenya.

However, access to training is not equivalent to training quality. One-off sessions may create awareness without supporting correct implementation or continued use. The frequency of training, practical relevance, trainer competence, availability of post-training guidance, and opportunities for farmer-to-farmer learning may determine whether knowledge is retained and applied. This distinction is important because adoption is behavioral and extends beyond attendance at a training event.

2.2 Diffusion of Innovations Theory

Diffusion of Innovations Theory explains adoption as a process that develops through communication over time within a social system. Adoption is influenced by perceived relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). Farmer training is relevant to each of these attributes. Training can explain the expected advantages of an innovation, demonstrate compatibility with local farming systems, reduce perceived complexity through guided practice, allow trial on demonstration plots, and make results observable. Peer learning also supports communication through trusted social networks.

The theory is useful because it connects training with farmers' understanding and evaluation of innovations. Nevertheless, its emphasis on individual perceptions can understate project-delivery constraints. Training may be well received but remain ineffective if sessions are infrequent, inputs are unavailable, or extension follow-up is weak. This study therefore treats training as both a learning process and a project-management arrangement embedded within implementation.

2.3 Conceptual Framework

The conceptual framework presents project management practices as independent variables that may influence the adoption of climate-smart agricultural innovations. The independent variables comprise project planning, resource allocation, training, and monitoring and evaluation. Project planning is represented by clear project objectives, stakeholder involvement, and climate integration; resource allocation by financial and material resources, extension support, and timely distribution; training by frequency, relevant content, and practical methods; and monitoring and evaluation by regular monitoring, feedback mechanisms, and evaluation of outcomes. The dependent variable is adoption of climate-smart agricultural innovations, reflected in uptake of the innovations, consistent use by farmers, and sustainability of practices.

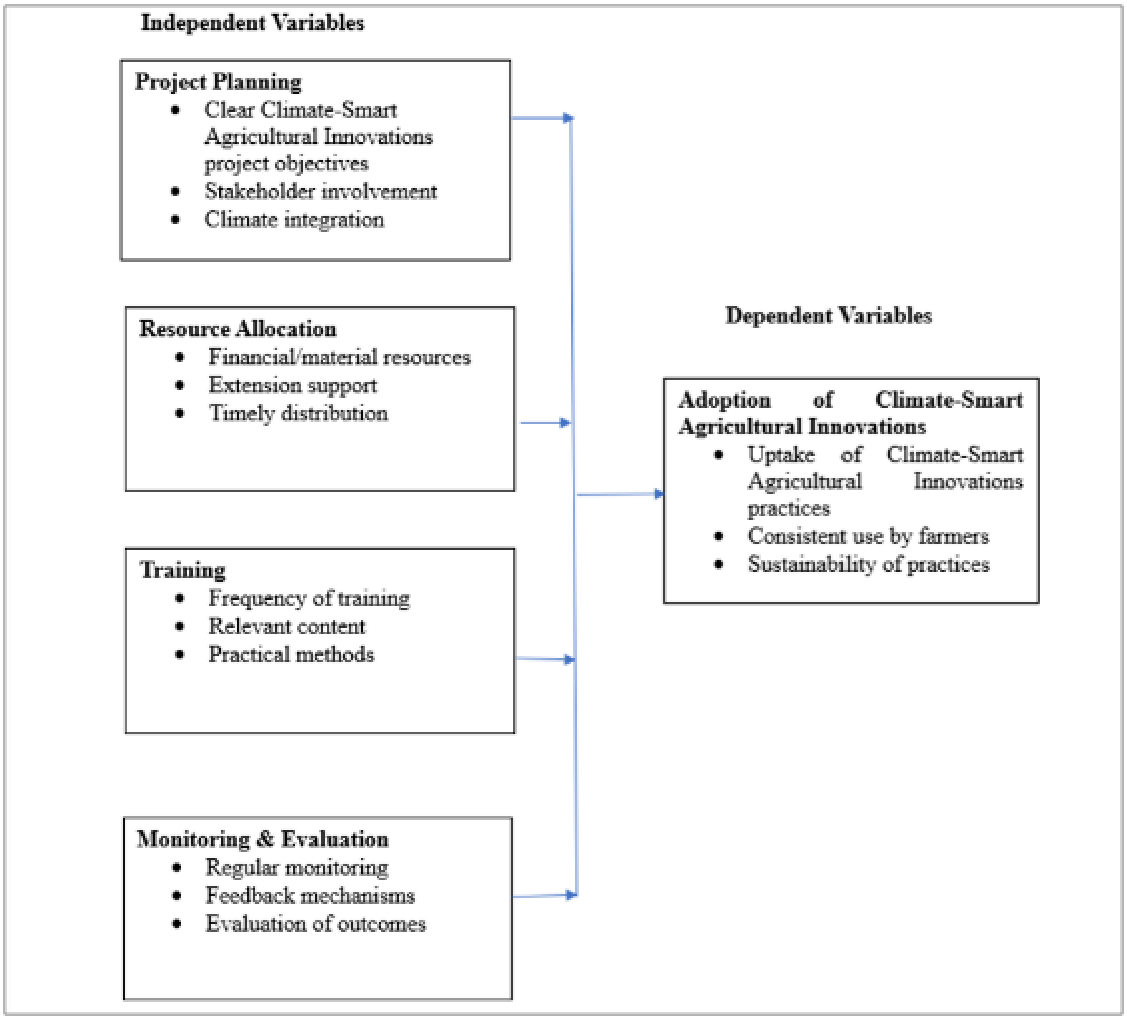

Figure 1: Conceptual framework showing the relationship between project management practices and adoption of climate-smart agricultural innovations.

The framework provides the broader project-management model underpinning the study. In this manuscript, farmer training is the focal independent variable, while project planning, resource allocation, and monitoring and evaluation are retained as control predictors in the multiple regression model. The framework therefore situates the specific analysis of farmer training within the wider project-management context while keeping the article's main analytical emphasis on the training–adoption relationship.

2.4 Research Hypothesis

The study tested the following null hypothesis:

- *H0: Farmer training has no statistically significant association with the adoption of climate-smart agricultural innovations among small-scale farmers.*

3 METHODOLOGY

3.1 Research Design and Study Area

The study used a descriptive cross-sectional research design. The descriptive component summarised respondents' assessments of training and adoption, while the cross-sectional component examined statistical relationships at one point in time. Qualitative evidence from key informants provided contextual interpretation and triangulation. The design supported conclusions about association and predictive contribution, but it did not establish temporal causation.

The research was conducted in Kalama Ward, Machakos County, Kenya. The ward comprises Kimutwa, Kaathi, Muumandu, Kyandii, and Makaveti administrative areas. The setting was selected because small-scale farmers in these areas had participated in climate-smart agriculture projects and could report on training and adoption experiences.

3.2 Population, Sample, and Sampling

The target population consisted of 600 small-scale beneficiary farmers identified from records held by the Machakos County Department of Agriculture, extension personnel, and implementing partners. Yamane's formula at a 5% margin of error produced a sample of 240 farmers. Multistage sampling was applied. Kalama Ward was purposively selected, the farmer sample was proportionately allocated across the five administrative areas, and eligible farmers were selected through computer-generated random numbers without replacement. Of the 240 questionnaires administered, 221 were returned and usable, representing a 92.1% response rate.

Eight key informants were purposively selected because of their involvement in climate-smart agriculture implementation. They comprised agricultural and project personnel with direct experience in farmer training. All eight planned interviews were completed.

3.3 Data Collection and Measurement

Quantitative data were collected using a structured questionnaire with a consistent five-point Likert scale, where 1 represented Strongly Disagree and 5 represented Strongly Agree. Farmer training was measured through seven retained items covering adequacy before implementation, improved understanding, practical relevance, continuous technical guidance, demonstration farms, knowledge sharing, and training frequency. Adoption was measured through seven items addressing uptake, consistent application, perceived productivity and resilience benefits, intention to continue, and willingness to encourage or recommend the innovations.

The questionnaire was pilot-tested with 24 farmers in a nearby area who were excluded from the main study. Ambiguous wording and item sequencing were refined. The farmer-training scale achieved a Cronbach's alpha of 0.869, while the adoption scale achieved an alpha of 0.881, indicating good internal consistency. A semi-structured interview guide was used for the qualitative component.

3.4 Data Analysis

Questionnaire data were checked, coded, and analysed using descriptive and inferential statistics. Frequencies, percentages, means, and standard deviations summarised the training indicators. Pearson's product-moment correlation assessed the direction and strength of the bivariate relationship between farmer training and adoption. Multiple linear regression assessed the unique contribution of farmer training while controlling for project planning, resource allocation, and monitoring and evaluation. Statistical significance was evaluated at alpha = 0.05. Interview records were reviewed, coded by objective, grouped into categories, and synthesised thematically. Qualitative evidence was used conservatively because verbatim de-identified transcripts were not part of the final examination package.

3.5 Ethical Considerations

Approval was obtained from the appropriate academic and administrative authorities before data collection. Participation was voluntary, respondents were informed of the purpose of the study, and confidentiality and anonymity were maintained. Personal identifiers were excluded from the analytical dataset, and information was used solely for academic purposes.

4 RESULTS

4.1 Respondent Participation

A total of 221 usable questionnaires were analysed from the 240 administered, giving a response rate of 92.1%. All eight key-informant interviews were completed. The achieved response levels were sufficient for the planned quantitative analysis and qualitative interpretation.

4.2 Descriptive Results for Farmer Training

Farmer training received a composite mean of 4.03 (SD = 0.86), indicating favourable assessments across the seven indicators. Improved understanding of climate-smart agricultural innovations received the highest rating (M = 4.13, SD = 0.80). Demonstration farms also received a strong rating (M = 4.08, SD = 0.83), followed by adequate training before implementation (M = 4.07, SD = 0.84). The lowest-rated indicator was the sufficiency of training frequency (M = 3.91, SD = 0.94), although the mean remained within the agreement range.

Table 1: Descriptive statistics for farmer training

Training indicator	M	SD
Adequate training before implementation	4.07	0.84
Training improves understanding of CSAI	4.13	0.80
Training is practical and relevant	4.03	0.86
Continuous technical guidance after training	3.97	0.91
Demonstration farms improve confidence	4.08	0.83
Training encourages knowledge sharing	4.02	0.87
Training frequency is sufficient	3.91	0.94
Composite score	**4.03**	**0.86**

The pattern suggests that training was most effective where it improved comprehension and allowed farmers to observe or practise the promoted innovations. The comparatively lower ratings for training frequency and continuous technical guidance indicate that follow-up and repetition may require strengthening.

4.3 Relationship between Farmer Training and Adoption

Pearson correlation showed a strong positive relationship between farmer training and adoption, $r = 0.741$, $p < 0.01$. Farmers who reported stronger training arrangements also tended to report higher uptake, continued application, and intention to maintain climate-smart agricultural innovations. The null hypothesis of no statistically significant association was therefore rejected.

Table 2: Correlation between farmer training and CSAI adoption

Variables	Farmer training	CSAI adoption
Farmer training	1	0.741**
CSAI adoption	0.741**	1

Note. ** Correlation is significant at the 0.01 level (two-tailed).

4.4 Unique Contribution of Farmer Training

The full regression model included project planning, resource allocation, farmer training, and monitoring and evaluation. The model was statistically significant, $F(4, 216) = 124.971$, $p < 0.001$, and explained 69.9% of the observed variation in adoption ($R^2 = 0.699$; adjusted $R^2 = 0.693$). Farmer training made the largest standardized contribution among the four predictors, beta = 0.378, $t = 5.836$, $p < 0.001$. Its unstandardized coefficient was $B = 0.356$, indicating that a one-unit increase in the training score was associated with a 0.356-unit increase in the adoption score when the other project-management practices were held constant.

Table 3: Regression results for farmer training

Predictor	B	SE	Beta	t	p	VIF
Farmer training	0.356	0.061	0.378	5.836	< 0.001	2.285

Note. Dependent variable: adoption of climate-smart agricultural innovations. The model controlled for project planning, resource allocation, and monitoring and evaluation.

4.5 Qualitative Interpretation

The key-informant evidence supported the quantitative pattern by emphasizing practical demonstrations, continued technical guidance, and opportunities for farmers to exchange implementation experience. Training was described as most useful when it moved beyond general awareness and showed farmers how to apply innovations within local conditions. Follow-up contact helped address implementation difficulties after initial instruction. The qualitative synthesis also reinforced the descriptive concern that insufficient training frequency can weaken continuity. Direct quotations are not presented because de-identified interview transcripts were not included in the available examination package.

5 DISCUSSION

The findings demonstrate a strong and statistically significant relationship between farmer training and the adoption of climate-smart agricultural innovations. The correlation coefficient of 0.741 indicates that training and adoption moved together strongly within the study sample. More importantly, training remained the strongest predictor in the multivariable model after accounting for planning, resources, and monitoring. This result suggests that training provides a distinct contribution rather than merely reflecting the general quality of project implementation.

The descriptive evidence clarifies how training may support adoption. Improved understanding received the highest score, indicating that farmers valued training as a means of making climate-smart innovations comprehensible. Demonstration farms also scored highly, consistent with the importance of observability and trialability in Diffusion of Innovations Theory (Rogers, 2003). By seeing practices applied and observing their results, farmers can evaluate feasibility before incorporating them into routine activities. Practical and relevant training may similarly reduce perceived complexity and improve compatibility with local production systems.

The findings align with research showing that access to training and extension services can strengthen agricultural technology adoption in Africa (Wossen et al., 2022). They also support the emphasis by FAO (2023) on continuing capacity development as part of climate-smart agriculture implementation. However, the present study adds a project-management perspective by treating training as a managed implementation function with design, timing, frequency, and follow-up requirements.

Training frequency received the lowest descriptive mean, while continuous guidance after training also scored below the composite mean. These results indicate that initial training alone may be insufficient. Farmers can encounter difficulties only after attempting to apply an innovation, particularly when climatic conditions, input availability, or farm characteristics differ from those used during instruction. Follow-up extension contact provides an opportunity to diagnose such challenges, reinforce correct practice, and adapt advice to specific circumstances.

The strong standardized coefficient should not be interpreted as proof that training causes adoption because the study was cross-sectional and relied partly on self-reported measures. Farmers who adopt more innovations may also seek more training or assess previous training more favourably. Nevertheless, the consistency of descriptive, correlational, regression, and qualitative evidence supports the practical importance of training within climate-smart agriculture projects.

6 CONCLUSION

Farmer training was strongly and positively associated with the adoption of climate-smart agricultural innovations among small-scale farmers in Kalama Ward. Training was the strongest predictor in the broader project-management model and was particularly valued for improving understanding, providing practical demonstrations, and strengthening confidence. The evidence indicates that training contributes most effectively when it is practical, relevant, repeated, and supported by continuing technical guidance. Climate-smart agriculture projects should therefore treat training as an ongoing implementation process rather than a single awareness event.

Recommendations

County agricultural departments and implementing organisations should expand demonstration-based training through farmer field schools, model plots, exchange visits, and guided on-farm practice. Training content should use locally relevant examples and should be scheduled around the agricultural calendar so that farmers can apply new skills when conditions are appropriate.

Project managers should provide structured post-training follow-up through extension visits, group mentoring, mobile advisory services, and farmer-to-farmer learning networks. Training plans should specify frequency, responsible personnel, learning outcomes, practical exercises, and mechanisms for responding to implementation difficulties.

Monitoring systems should assess more than attendance. They should track knowledge gained, ability to demonstrate the promoted practice, initial uptake, correct application, continued use, and the support required after training. This approach would allow project teams to identify weak learning outcomes early and take corrective action.

Limitations and Further Research

The cross-sectional design identified associations but could not establish temporal order or causation. Training and adoption were measured through self-reported questionnaire responses, creating possible recall, social-desirability, and common-method bias. The research was limited to one ward, and the findings should not be treated as statistically representative of every small-scale farmer in Machakos County or Kenya. Although key-informant evidence supported interpretation, verbatim interview transcripts were unavailable for quotation in the manuscript.

Future studies should use longitudinal or quasi-experimental designs to examine whether training precedes and sustains adoption over time. Comparative research could test the relative effectiveness of demonstration plots, farmer field schools, digital extension, peer learning, and blended training. Further analysis should also consider whether education, farm size, access to inputs, gender-related resource constraints, and extension intensity modify the relationship between training and adoption.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Acknowledgments

The authors sincerely appreciate the participating farmers, key informants, agricultural personnel, and implementing organisations for their cooperation, valuable contributions, and support during the study. The authors also acknowledge all individuals and institutions that provided assistance during the implementation of the study and contributed to its successful completion

Funding Source

The underlying postgraduate study received partial financial support from the Hanns Seidel Foundation (Employer), with the remaining costs being self-funded by the author. The funder had no role in the study design, data collection, analysis, interpretation of the findings, or preparation of the manuscript.

Disclosure of conflict of interest

The author declares no known competing financial interests or personal relationships that could have influenced the work reported in this manuscript.

Data Availability Statement

The data supporting the findings contain information collected from study participants and are not publicly deposited. Access may be considered for legitimate academic purposes subject to applicable ethical, institutional, and confidentiality requirements.

REFERENCES

[1] Food and Agriculture Organization of the United Nations. (2023). Climate-smart agriculture sourcebook (3rd ed.). FAO.

[2] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2022). Multivariate data analysis (8th ed.). Cengage Learning.

[3] Intergovernmental Panel on Climate Change. (2022). Climate change 2022: Impacts, adaptation, and vulnerability. Cambridge University Press. https://www.ipcc.ch/report/ar6/wg2/

[4] Mugambi, I., Wambugu, S., & Kirimi, L. (2021). Determinants of adoption of climate-smart agriculture technologies among smallholder farmers in Kenya. African Journal of Agricultural Research, 17(4), 567–576.

[5] Muriithi, B. W., et al. (2021). Institutional factors influencing adoption of climate-smart agriculture in Kenya. African Journal of Agricultural and Resource Economics, 16(2), 85–101.

[6] Mwongera, C., Shikuku, K. M., Twyman, J., Läderach, P., Ampaire, E., Van Asten, P., Twomlow, S., & Winowiecki, L. (2017). Climate-smart agriculture rapid appraisal (CSA-RA): A prioritization tool for out-scaling climate-smart agriculture. Agricultural Systems, 151, 192–203.

[7] Njuguna, E., Mwangi, M., & Ngigi, M. (2022). Factors influencing adoption of climate-smart agriculture technologies in Kenya. Climate and Development, 14(6), 512–523. https://doi.org/10.1080/17565529.2021.1971943

[8] Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.

[9] Project Management Institute. (2021). A guide to the project management body of knowledge (PMBOK guide) (7th ed.). Project Management Institute.

[10] Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

[11] Wossen, T., Abdoulaye, T., Alene, A., & Manyong, V. (2022). Impacts of extension access and training on adoption of agricultural technologies in Africa. Food Policy, 110, 102277.

[12] Yamane, T. (1967). Statistics: An introductory analysis (2nd ed.). Harper & Row.