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Cluster Analysis-Based Discernment of Farmers' Typologies and Climate Change Adaptation Strategies among Rural Women

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HIGHLIGHTS

- Identified four farmer clusters emphasizing diverse climate adaptation strategies through K-means clustering.
- Highlighted cluster-specific priorities: agronomic practices, mechanization and technology integration, soil and water management practices, and sustainable and eco-friendly practices.
- Recommended targeted interventions for climate resilience and empowerment of rural women farmers.

ARTICLE INFO

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ABSTRACT

Climate change poses significant challenges to agriculture, particularly in vulnerable regions like Uttar Pradesh and Haryana, where women contribute significantly to the agricultural workforce. They play a pivotal role in adopting climate-smart adaptation strategies ensuring food security, economic stability, and environmental sustainability. The study was conducted in 2024 to explore women farmers 'adaptation strategies using K-means clustering. Based on their prioritization of 16 strategies, randomly selected 100 women farmers were found to belong in four distinct clusters. Cluster 1 emphasized crop and agronomic practices, changing planting dates, crop rotations, and Direct Seeded Rice (DSR). Cluster 2 prioritized mechanization and technology integration, raised-bed planting and laser levelling. Cluster 3 focused on soil and water management and harvesting practices, zero tillage, crop diversification, while Cluster 4 preferred sustainable practices as mulching, Integrated Pest Management (IPM), and bio-fertilizers. The analysis underscores the need for targeted agricultural and extension interventions tailored to each cluster's unique priorities. Strategies include promoting climate-resilient crops, precision agriculture, conservation techniques, and bio-inputs. Extension approaches such as field demonstrations, custom hiring centers, and capacity-building workshops are recommended. These findings highlight importance of cluster-specific strategies to empower women farmers and enhance their resilience to climate change, contributing to sustainable development goals.

INTRODUCTION

Agricultural production systems worldwide are expected to undergo transformations in response to changing climatic conditions, as evidenced by studies linking recent variations in crop yields to the impacts of climate change (Harikrishna et al., 2019; Ray et al., 2015; Sarkar et al., 2022). The Economic Survey 2022-23 highlights that 65 per cent of India's population resides in rural areas, with nearly 47 per cent depending on agriculture for their livelihoods. Agriculture is the primary income source for 70 per cent of rural households, of

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which 82 per cent are small and marginal farmers. Sustainable development, balancing human well-being with ecological constraints, is critical. The UN's Human Development Index (HDI) and Ecological Footprint measure progress toward this goal. The 2030 Agenda for Sustainable Development, encompassing 17 goals, underscores the significance of gender equality. Empowering rural women, who constitute 80 per cent of India's agricultural workforce, is crucial for economic growth, food security, and poverty reduction (Renu, 2023). India's Azaadi Ka Amrit Mahotsav, celebrating 75 years of independence, emphasizes the empowerment of women, acknowledging their pivotal role in rural development. Climate change, characterized by rising global temperatures and extreme climatic events, poses a significant threat to ecosystems and human livelihoods. Its impacts are felt worldwide, but rural communities, especially women, are among the most vulnerable (Bharat et al., 2022).

Rural women face significant challenges, including financial instability, socio-economic vulnerabilities, and climate variability, all of which exacerbate poverty. Climate change disproportionately affects vulnerable populations reliant on agriculture. In India, droughts impact over 21 per cent of the land, and climate-induced health issues and economic losses are projected to rise by 2030 (Chuphal et al., 2024). Addressing these challenges requires prioritizing SDG 5 – Gender Equality. Despite efforts like the Drought Early Warning System (DEWS), action remains urgent. Women's vulnerability is compounded by poverty, limited resource access, and socio-cultural norms, particularly in rural areas where they spend considerable time fetching water and firewood. Climate-related events like droughts and floods heighten these burdens. Studies show that women from underprivileged backgrounds in arid regions are disproportionately affected (Yadav & Lal, 2018). Limited education, institutional support, and socio-cultural constraints further hinder adaptation. However, women also act as agents of change, applying knowledge and adaptive strategies. Initiatives such as community seed banks and rainwater harvesting empower women to manage resources sustainably, enhancing resilience and social status.

Zhang et al., (2020) identified barriers to adaptation, inadequate technology, financial constraints, and poor infrastructure, noting socio-economic factors like education, experience, and gender influenced strategies. Health-related climate risks led to financial adaptations, while agricultural concerns prompted diversification. Goli et al., (2020) found that threat and coping appraisals shaped adaptation, severity perceptions affecting threat appraisal and response costs influencing coping. Djoudi & Brockhaus (2011) highlighted gendered adaptation differences, where male migration increased women's workloads. Similarly, Khalil et al., (2020) observed that male migration in Gabura empowered women to adopt innovations by collaborating with aid agencies & leveraging social capital.

This study seeks to understand the diverse characteristics and climate change adaptation strategies of female farmers in rural areas through cluster analysis, offering insights to enhance gender-sensitive adaptation strategies for sustainable development.

METHODOLOGY

The study was conducted in Uttar Pradesh and Haryana, chosen for their high vulnerability to climate change. Uttar Pradesh, with over 250 million people, 58,000 Gram Panchayats, and 750 Urban Local Bodies, frequently faces floods, cold waves, and heat waves. Approximately 50 of its 75 districts are highly to moderately vulnerable. Haryana, a semi-arid state integral to India's Green Revolution, has experienced severe climate impacts, including damage to 347,117 hectares of agricultural land (Kaur et al., 2021). Two districts were randomly selected from each state: Mathura in Uttar Pradesh and Nuh in Haryana. A sampling frame of women farmers engaged in agriculture was created, and 50 farmers from each district were selected through simple random sampling.

Primary data was collected through personal interviews and Focus Group Discussions (FGDs), which identified key variables. A structured questionnaire captured socio-personal characteristics and climate-smart adaptation strategies adopted by respondents. Adaptation strategies were scored on a binary-ordinal scale, with '2' assigned to practiced strategies and '1' to unpracticed ones. These socio-personal variables were closely tied to the adaptation measures adopted for mitigating climate change effects. Cluster analysis served as the primary method to achieve the study's objectives. Multiple iterations were conducted to identify the optimal number of clusters by analyzing variations in mean distances between initial clusters (Blashfield & Aldenderfer, 1978). The non-hierarchical K-means algorithm was utilized to group farmers with similar adaptation strategies. This approach enabled the identification of distinct target groups, allowing for the promotion of climate-smart practices tailored to their needs, ultimately enhancing their capacity to adopt effective strategies for climate change adaptation (Mabon et al., 2021). The K-means algorithm is a widely used clustering method that generates a single set of flat clusters without hierarchical organization. It is suitable for datasets with distinct groups but requires the number of clusters (K) to be predetermined. This selection often involves trial and error due to its subjective nature. Therefore, for clustering, both the hierarchical and non-hierarchical clustering function in SPSS was employed. Hierarchical Clustering was used to judge the number of clusters and the clustering quality was checked through two step cluster and finally K-means clustering was done for creating the different groups. Additionally, discriminant analysis was used to evaluate the ability of the variables to predict the classification of respondents into clusters. To ensure the results' accuracy, canonical discriminant analysis was conducted for data verification (Carvalho et al., 2015).

RESULTS

Hierarchical cluster analysis was used to examine whether the 16 adaptation strategies enabled effective farmer segmentation. From the dendrogram,4 clusters were estimated, which was further validated through Two-step clustering method for the optimal number of clusters by evaluating the Silhouette measure of Cohesion and separation (Figure 1). A value 0.5 with four clusters showed a fair clustering. The value decreased on addition or deletion of a cluster; hence, four clusters were considered appropriate. Further K-means clustering based on centroid method was used for final segmentation. The four identified clusters and the number of farmers in each cluster are presented in Table 1. Cluster 4 had the highest representation with 41 members, followed by Cluster 1 with 31,

Table 1. Number of cases in each cluster

Cluster Number	No. of respondents
1	31
2	18
3	10
4	41

Figure 1. Silhouette measure for optimal number of clusters

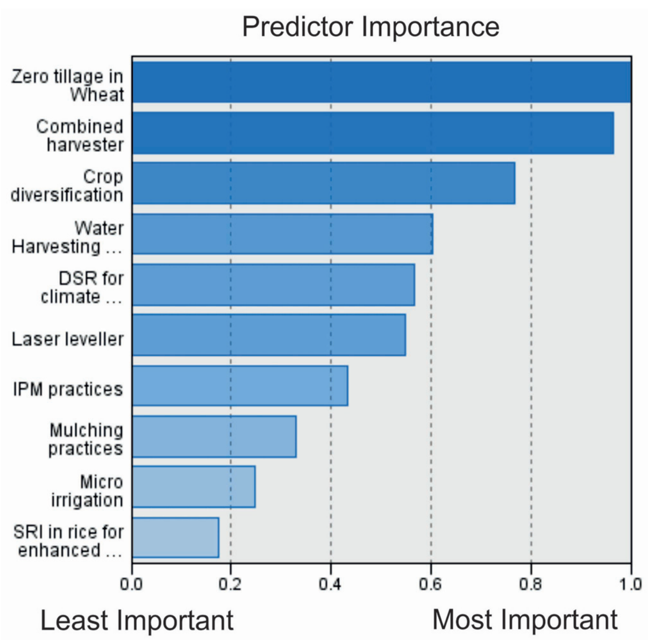

Figure 2. Relative importance of predictors in clustering

Cluster 2 with 18, and Cluster 3 with 10 members. The distribution highlights variability in group sizes, indicating diverse adaptation patterns among respondents. The relative importance of various predictors in determining clusters in a two-step cluster model is illustrated in Figure 2. Zero tillage in wheat is the most influential predictor, followed by the use of combined harvesters and crop diversification, indicating their significant role in defining cluster groupings. Water harvesting structures and Direct Seeded Rice (DSR) for climate adaptation also have moderate importance, emphasizing their relevance in distinguishing groups. Predictors like System of Rice Intensification (SRI) and micro-irrigation are the least important, suggesting they have minimal impact on cluster formation. Overall, the model prioritizes practices that focus on sustainable land use and mechanization.

The K-means clustering analysis grouped respondents into four distinct clusters based on the importance they assigned to various adaptation strategies, reflecting unique patterns and preferences (Table 2). Cluster 1 (Mean: 1.77) demonstrated a notable emphasis on Changes of planting dates, Changes of varieties, Practising crop rotations, Direct Seeded Rice and Systematic Rice Intensification. This indicates an adoption of crop and agronomic practices. Respondents in Cluster 2 (Mean: 1.54) prioritized raise-bed planting, laser leveller and combined harvester, highlighting a strong preference for Mechanization and Technology integration. Cluster 3 (Mean: 1.60) placed the greatest emphasis on Soil and water management practices, such as Zero tillage, Crop diversification, Water Harvesting Structure and Micro irrigation showcasing their importance in enhancing resilience. Members of Cluster 4 (Mean: 1.69) showed a sustainable and eco-friendly practices, with high importance placed on Mulching IPM practices, and Bio-fertilizers. This group reflects a preference for strategies that integrate sustainability and innovation.

Table 2. Mean values of the adaptation strategies in different clusters

Adaptation Strategies	Cluster			
	1	2	3	4
Change planting date/periods	1.98	1.39	1.63	1.83
Changes of varieties	2.00	1.72	1.70	1.95
Changes of planting dates	2.00	1.79	1.80	1.83
Raise-bed planter	1.89	2.00	1.80	1.95
Zero tillage in Wheat	1.74	1.00	2.00	1.10
Crop diversification	1.32	1.61	2.00	1.95
Mulching practices	1.71	1.29	1.16	1.89
Laser leveller	1.32	1.55	1.33	1.20
Practising crop rotations	1.83	1.61	1.70	1.80
Water Harvesting Structure	1.48	1.89	2.00	1.78
Micro irrigation	1.81	1.78	1.98	1.55
DSR for climate adaptation	1.93	1.33	1.00	1.69
SRI in rice for enhanced production	1.78	1.00	1.27	1.44
IPM practices	1.74	1.46	1.40	2.00
Bio fertilizers	1.66	1.50	1.80	1.81
Combined harvester	1.94	2.00	1.00	1.34
Two Step Cluster Number	4	2	6	1
Cluster Mean	1.77	1.54	1.60	1.69

The results of one-way ANOVA reveal variations in socio-personal variables across the four clusters, highlighting significant differences for a few variables while most remain statistically non-significant (Table 3). A significant F-value (3.281) suggests that landholding size varies notably among clusters, with Cluster 2 having the largest average landholding (1.648 acres) and Cluster 3 the smallest (0.779 acres). A significant F-value (2.967) implies that access to market information differs across clusters, with Cluster 1 having the highest mean (1.58) and Clusters 2 and 3 the lowest (1.22 and 1.20, respectively). A substantial difference is observed in annual income (F = 5.204*), where Cluster 3 has the highest average income (1.92), while Clusters 1 and 2 report lower incomes (1.42 and 1.39, respectively). The variables like age, education, family size, number of earners in the family, access to training, and market distance have non-significant F-values ($p > 0.05$). This indicates that there are no substantial differences in these characteristics across the clusters.

To ensure accurate clustering in this study, canonical discriminant analysis was performed. The verification was carried out on 4 clusters and 16 variables which were the adaptation strategies. Discriminant analysis is primarily used to predict group

Table 3. Socio-personal characteristics of Cluster-Based on Mean and Standard Deviation

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4	F value (ANOVA)
Age (years)	31.61(3.25)	33.33(7.62)	38.20(11.73)	34.63(10.65)	1.69^{ns}
Education (years)	2.55(0.96)	3.11(1.41)	2.60(0.70)	2.59(0.92)	1.38^{ns}
Family size (No. of members)	8.26(4.12)	9.83(4.84)	9.90(3.48)	9.29(4.55)	0.69^{ns}
No. of people earning in the family (Nos.)	1.65(1.33)	2.56(1.85)	2.10(0.74)	2.20(1.60)	1.53^{ns}
Land holding size (acres)	1.10(0.95)	1.65(0.86)	0.78(0.73)	1.31(0.98)	3.28*
Access to Training (1=No, 2=Yes)	1.26(0.45)	1.17(0.38)	1.40(0.52)	1.22(0.42)	0.68^{ns}
Market distance (kms)	8.23(3.78)	9.17(3.09)	8.50(2.42)	8.39(2.88)	0.36^{ns}
Market Information (1=No, 2=Yes)	1.58(0.50)	1.22(0.43)	1.20(0.42)	1.37(0.49)	2.97*
Annual income (Rs. lakh)	1.42(0.53)	1.39(0.56)	1.92(0.78)	1.57(0.58)	5.20*

Note: *significant at p-value <0.05; ^{ns}Not significant

membership among two or more mutually exclusive categories (Backhaus et al., 2023). Three discriminant canonical functions were identified in the canonical discriminant analysis (Table 4). The results in Table 4 show the effectiveness of these functions in distinguishing between groups. Function F1, with eigenvalues greater than 1, account for 57.5 per cent of the total variance, while the remaining functions contribute only a small percentage to explaining the variance in the analysis. An eigenvalue reflects the proportion of variance explained (the ratio of between-groups sums of squares to within-groups sums of squares). A larger eigenvalue (>1) indicates a stronger function, and in this case, the values are strong. The analysis showed that three discriminant functions had a canonical correlation of 0.744, 0.564 and 0.556 respectively. The canonical correlation, measures the relationship between discriminant scores and the levels of the dependent variable, was high for the function F1 0.744 (with 1.00 being perfect), indicating that the function discriminates very effectively.

Wilks' Lambda is the ratio of within-group sums of squares to the total sums of squares, representing the proportion of variance in the discriminant scores that is not explained by the differences between groups. A Wilks' Lambda value of 1.00 suggests that the group means are equal, meaning all the variance is explained by factors other than the differences between means. A smaller Lambda value indicates that the within-group variability is small in comparison to the total variability, suggesting significant differences between group means (Harlow & Duerr, 2013). As represented in Table 5, Wilks' Lambda in three tests of functions were significant at p<0.01 with values of 0.211, 0.471, and 0.690 respectively which is very low, indicating that the group means differ significantly.

Table 4. Eigen value of Canonical Discriminant Analysis

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
F1	1.236[a]	57.5	57.5	0.744
F2	.465[a]	21.6	79.1	0.564
F3	.448[a]	20.9	100.0	0.556

a. First 3 canonical discriminant functions were used in the analysis.

Table 5. Wilks' Lambda value of Canonical Discriminant Analysis

Test of Function(s)	Wilks' Lambda			
	Wilks' Lambda	Chi-square	df	Sig.
1 through 3	0.211	138.600	48	0.000
2 through 3	0.471	66.973	30	0.000
3	0.690	32.964	14	0.003

DISCUSSION

Four different farmer groups were identified by the K-means cluster analysis according to how they prioritised adaptation strategies. This underscores the necessity of customised agricultural and extension interventions to improve climate change adaption. The crop and agronomic techniques that were highlighted in Cluster 1, which had the highest Mean score (1.77), including crop rotation, Direct Seeded Rice (DSR), System of Rice Intensification (SRI), modifying planting dates, and adopting enhanced crop types. The emphasis on improving crop management to deal with climatic unpredictability is seen in these tactics. For this cluster, promoting climate-resilient crop varieties, optimizing planting schedules using weather forecasts, and enhancing training on DSR and SRI techniques are critical agricultural strategies. Extension activities could include field demonstrations, mobile advisory services, and farmer-to-farmer learning networks to facilitate wider adoption (Bakhsh & Feil, 2021). Cluster 2 (Mean: 1.54) demonstrated a strong preference for mechanization and technology integration, including raised-bed planting, laser levelling, and combined harvesters. These farmers prioritize efficiency and productivity gains through technology. Agricultural strategies for this group should focus on facilitating access to mechanized tools through subsidies or cooperative models and promoting precision agriculture technologies. Extension approaches, such as custom hiring centres, field demonstrations, and collaborations with agricultural technology providers, can further enhance technology adoption. Cluster 3 (Mean: 1.60) highlighted the importance of soil and water management practices, including zero tillage, crop diversification, water harvesting structures, and micro-irrigation systems. These strategies reflect a focus on resource conservation to build resilience. Agricultural interventions should prioritize conservation agriculture techniques, diversified cropping systems, and the establishment of community-managed water harvesting structures. Extension efforts could involve capacity-building workshops, subsidies for micro-irrigation systems, and community-based water management models to improve the adoption of these practices (Kumar et al., 2020). Cluster 4 (mean: 1.69) showed a preference for sustainable and eco-friendly practices, emphasizing mulching, Integrated Pest

Management (IPM), and bio-fertilizers. This cluster aligns with a sustainability-focused approach to adaptation. Agricultural strategies should promote bio-fertilizers, bio-pesticides, and mulching to enhance soil health and reduce chemical dependency. Extension strategies could include demonstration plots, farmer schools, and improved access to certified bio-inputs. Resource allocation becomes more efficient, prioritizing areas with vulnerable groups for investments in climate-resilient infrastructure (LaFevor, 2022). These findings underscore the heterogeneity in farmers' adaptation preferences, influenced by their agro-ecological and socio-economic contexts. By aligning agricultural and extension strategies with the specific needs and priorities of each cluster, policymakers and practitioners can foster the adoption of climate-smart practices, enhancing resilience and sustainability in farming systems.

CONCLUSION

Policymakers should ensure access to climate-resilient seeds, improved crop varieties, and water-efficient technologies, alongside subsidies for practices like zero tillage, crop diversification, and micro-irrigation. Extension services should offer tailored strategies for different farmer groups, focusing on women's specific vulnerabilities related to land tenure and access to resources. Training programs on sustainable practices, including pest management and water harvesting, should emphasize women-centered approaches, such as self-help groups and farmer field schools. Research should focus on affordable, labor-saving technologies for women, like portable water systems and lightweight mechanization. The private sector can support this by providing affordable bio-inputs, machinery, and financing for women's cooperatives. NGOs and civil society should advocate for resource equity and capacity-building initiatives. These efforts, if well-coordinated, will empower women and enhance agricultural resilience to climate change.

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