

PERCEIVED EFFECTIVENESS AND UPSCALING POTENTIAL OF CLIMATE-SMART AGRICULTURAL INTERVENTIONS ACROSS FARM TYPOLOGY

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ABSTRACT

Understanding heterogeneity among farmers based on socio-economic characteristics and resource endowments is essential for developing farm typologies and thus strategically promoting effective climate-smart agriculture (CSA) interventions in climatically vulnerable regions. This study applied a participatory approach to measure the effectiveness and upscaling potential of CSA interventions based on farmers' preferences in a drought-prone region of Wayanad, Kerala, using 146 farmer respondents. Using principal component and cluster analysis, four typologies were identified from the region based on socio-economic characteristics: resource-intensive crop farmers, diversified household-oriented farmers, marginal crop farmers, and livestock-oriented farmers. The results indicated that resource-intensive farmers perceived the highest effectiveness in using interventions such as water management and machinery in farm operations, as it improved their resilience to climate shocks. However, the scalability of interventions was highly identified for the resource-poor and less diversified typology of marginal crop farmers and livestock-oriented farmers. Thus, this study highlights that to improve the benefits and scalability of CSA interventions, the implementation should be based on typology, understanding the diversity rather than a blanket model of implementation.

KEYWORDS: Farm typology, climate-smart agriculture, adoption, effectiveness, upscaling potential

INTRODUCTION

Agriculture operates under the dynamic influence of climate vagaries, and it severely affect agricultural production during extreme events. For drought-affected regions, the burden becomes acute as water resources become stressed, and it makes agriculture a less reliable option (Khatun et al., 2025). It hinders crop productivity, reducing income generation and increase risk in the livestock sector. These impacts, particularly on economically backward regions, where the majority of the population depends on agriculture for a living, can worsen food security, livelihoods, and thus increase poverty (Shirsath et al., 2017). To address these challenges, climate-smart agriculture (CSA) interventions were positioned as a capable strategy to transform the current agricultural system in a changing climate, while ensuring productivity, improving resilience, and reducing greenhouse gas emissions (FAO, 2013; Kabato et al., 2025). Along with these, income was added as the fourth potential, giving immediate benefits to farmers, thus together with productivity, resilience, and mitigation as the four pillars of CSA practices (Khatri-Chhetri et al., 2019; Singh et al., 2021). There is a bundle of CSA practices and technologies, from drought-tolerant crop varieties to precision agriculture systems and climate-informed decision support technologies, to buffer farmers from climate risks (Khatun et al., 2025). It is not just a set of practices that can be applied universally, but requires identifying and understanding the region, agricultural landscape, resource endowments, and the requirements of farmers based on socio-economic characteristics before implementing the best CSA practices. In India, National Innovations on Climate Resilient Agriculture (NICRA) has been formed to identify, support, and implement suitable CSA practices in different vulnerable districts across India since 2011. Despite many years of initiatives to promote CSA in the country, the adoption level still remains poor (Aryal et al., 2018).

The blanket suggestion of CSA practices without addressing the agro-ecological and socio-economic environment of the farmers has remained the main issue for many years, leading to poor adoption and scalability. This can be due to policymakers' and development actors' inability to address the heterogeneity among farmers in terms of socio-economic characteristics, resources owned, agroecology, and management practices. Local complexities and diversities at the farm level are often undervalued, resulting in indeterministic results. Interventions that are framed to give blanket solutions have failed to deliver long-lasting sustainable outcomes for heterogeneous farming systems (Chang, 2012). Identifying the key differences and the characteristics of different farmers and farm systems helps to simplify the large diversity, thereby providing precise interventions and policy support to the farmers (Goswami et al., 2014). To date, only a few studies have attempted to measure the diversity among farmers to frame effective policies and strategies. This makes a compelling case for understanding CSA adoption by different farm typologies, rather than the one-size-fits-all nature of implementing CSA interventions.

In parallel, it is equally important to understand the effectiveness of the interventions to evaluate them, which enables development agencies to fill the gap. The existence of diverse CSA practices does not guarantee their high impact for adopters. It's equally important to acknowledge farmers' satisfaction with the various interventions adopted by them to ensure their sustained use. Otherwise, the large capital invested in the promotion and implementation of CSA practices and farm resources will be misspent. The policy-level strategies and decisions often fail to be realistic and functional without farmers' satisfaction (Azadi et al., 2021). The responsibility of policymakers, scientists, and extension personnel towards farmers does not just remain in disseminating and evaluating the technology developed. Once the farmer realizes the effectiveness of a practice, he should be able to continue it and upscale the usage for his betterment. Upscaling of CSA technology is crucial for the replication and adaptation of it to achieve an increased scale of impact. Upscaling also works on reframing the strategies to bridge the gap between the desirable change expected by farmers and the improvement envisioned by policymakers. The effectiveness and upscaling potential of any intervention is influenced by the livelihood indicators under physical, social, financial, human, and natural assets. Therefore, the promotion of CSA practices requires farm typology-specific, effective options with upscaling potential as well as institutional arrangements.

This study attempted to capture the complexity and heterogeneity among farmers based on their characteristics to define them into particular homogeneous clusters, and importantly integrated this understanding in exploring the pathways for CSA practices intensification. The given framework also integrates the assessment of various CSA interventions through effectiveness and upscaling potential. Using a participatory approach, an understanding is developed of the above and the specific constraints faced by each of the identified farm types. The objectives of the study are:

To describe the general characteristics of farmers to identify farm typologies

To analyse the CSA interventions adopted across typologies and measure the perceived effectiveness and upscaling potential of CSA interventions across farm typologies

METHODOLOGY

Locale of the study and sampling

The study area, Padichira village of Wayanad district, Kerala, was purposively selected as it is a drought-prone area, where the National Initiative on Climate Resilient Agriculture (NICRA) project of ICAR has been implemented since 2022 (Figure 1). This area receives the lowest amount of rainfall in Wayanad district and experiences water scarcity, especially during summer, which has adversely affected the plantation crops like pepper, coffee, and areca nut. The village has unique and diverse agro-ecological conditions, farming systems, and socio-economic contexts relevant to framing farm typology. Key descriptive details of the village are given in Table 1.

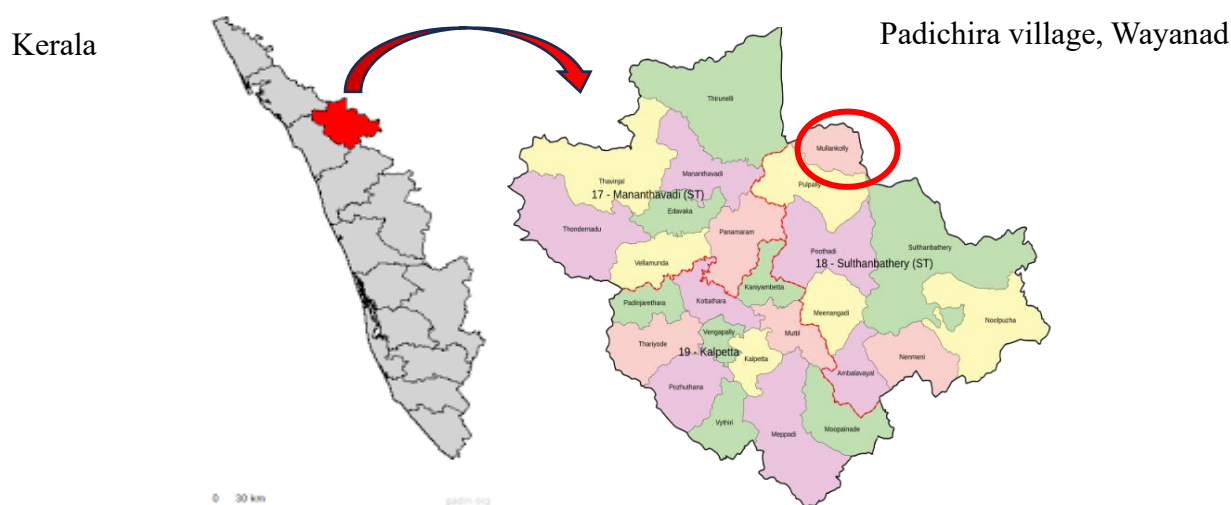


Figure 1. Locale of the study region in Wayanad

Table 1. Biophysical setting of Padichira village

Details of the area studied: Padichira (2024-25)	
No. of households	838
Cultivated area (ha)	186
Rainfed area (ha)	104
Irrigated area (ha)	82
Drought-affected area (ha)	104
Mean annual temperature (°C)	25.5 ±2
Annual rainfall (mm)	775

Source: KVK & RARS, Ambalavayal (Annual Report)

A list of CSA interventions was identified based on NICRA project analysis and consultation with project coordinators of the region. We considered the major interventions from the local region, which were adopted by the majority, for evaluation. A stratified purposive sampling method with proportional allocation was employed to capture the diversity of farm households, ensuring representation of farmers adopting different CSA interventions through preliminary assessments. A total of 146 households were surveyed, and data were collected for the reference agricultural year 2024–2025, conducted during June 2025 using structured questionnaires and participatory discussions, supplemented by key informant interactions from Krishi Vigyan Kendra, Ambalavayal, to validate responses (Table 2).

Table 2. Selected CSA interventions to assess farmers' perceived effectiveness and upscalability

CSA intervention	Adaptation and mitigation potential	Number of farmers surveyed
Water Management		
1. Micro-irrigation in coffee plantations	Application of water precisely to minimize water loss and improve efficiency	20
2. Construction of percolation pits	Collection of rainwater, not allowing it to run off and allowing it to percolate on-site.	23
Crop Management		
3. Cultivation of drought-tolerant cowpea variety – VBN3	Varieties that are tolerant to drought/heat stress and require less water	20
4. Summer cropping in rice fallows using Sesame	Allowing efficient land use through crop diversification during the drought period	13
Mechanization in Farm Operations		
5. Mechanization in planting and intercultural operations through custom hiring center	Accessibility and affordability of improved machinery, reducing farm drudgery and cost	25
6. Use of drone technology	Optimizing input usage and reducing water use for fertilizer application	25
Livestock Support		
7. Cattle fed with mineral mixture	Reducing vitamin and mineral deficiency and thus improving the yield of cattle	20

Analytical techniques

Farm typology framing

Principal Component Analysis (PCA) and Cluster Analysis (CA) were employed systematically to identify and construct distinct farm typologies within the study area (Usai et al., 2006; Kumar et al., 2019). PCA was first used to reduce the dimensionality of the dataset by extracting key components that explain the maximum variance among studied variables related to farm structure, income, assets, and socio-economic characteristics (Table 3). The principal components helped in capturing underlying patterns in the data while minimizing redundancy. The PCA transformation (Abdi & Williams, 2010) is a common multivariate statistical method that is used for feature extraction and dimensional reduction in pattern analysis. Its goal is to extract important information from data and decrease the dataset volume by maintaining the important information and simply explaining the dataset and analysis of observations.

Assume X is the input dataset ($X = X_1, X_2, X_3, \dots, X_{13}$) where every column is a d -dimensional input pattern. Further assume that the average of each feature in the dataset is equal to zero ($E(X) = 0$). An orthonormal transformation can be used to map X into the new space Y as:

$$Y = AX \quad (\text{Eq. 1})$$

Table 3. Variables used to categorize farmers according to typology

Variable	Description
X1	Age of the household head in years
X2	Household size in numbers
X3	Total land possessed in acres
X4	Gross cropped area during the year in acres
X5	Gross irrigated area in the year in acres
X6	Livestock units in numbers
X7	Farm machinery and implements owned in monetary terms ('000Rs)
X8	Crop income received in rupees ('000Rs) for the year
X9	Livestock income in rupees ('000Rs) for the year
X10	Non-farm income in rupees ('000Rs) of the family
X11	Family consumption expenditure in rupees ('000Rs)
X12	Number of conveyance units in the family

Assuming that $E(X) = 0$, the $E(Y) = 0$ and the Y covariance matrix is:

$$R_y = AR_xA^T \quad (\text{Eq. 2})$$

where R_x is the covariance matrix of X . If the rows of A are eigenvectors of R_x , then using this transformation, the samples become uncorrelated in the new space. The samples are d -dimensional in the feature space (mapped space). However, the goal of the PCA transform is to create $k < d$ -dimensional mapped samples which will approximate X well. Using Eq. (1), X can be recreated as

$$X = A^TY \quad (\text{Eq. 3})$$

Instead of reproducing X using all eigenvectors, it can be estimated with fewer eigenvectors; thus,

$$\hat{X} = A_k^TY \quad (\text{Eq. 4})$$

where k eigenvectors are used.

If $\hat{X}$ is reproduced using the corresponding eigenvectors with the biggest eigenvalues, the minimum error is reproduced. The appropriateness of the dataset for PCA was also verified previously using Bartlett's test of sphericity and the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy.

Subsequently, CA using hierarchical methods grouped farm households into homogeneous clusters based on their scores from the PCA. These clusters represented typologies that differed in terms of landholding size, asset ownership, cropping pattern, income levels, and technology adoption. The integrated use of PCA and CA enabled the identification of functionally distinct farm groups, facilitating targeted analysis of technology effectiveness and scalability across typologies. CA groups the observations according to the similarity among their attributes. As a result, the observations within a cluster are more similar than observations between clusters as measured by the clustering criterion. CA groups the observations into categories based on the characteristic variables. The categories are unknown in CA.

A key element in deciding assignment of observations to clusters is “attributive distance.”. The most commonly used attributive distance measure is Euclidean distance:

$$d_{ij} = \left(\sum_{k=1}^K (x_{ik} - x_{jk})^2 \right)^{1/2} \quad (\text{Eq. 5})$$

where x_{ik} and x_{jk} are the k th variable of the K -dimensional observations for individuals i and j , respectively.

Measuring effectiveness of CSA interventions

To assess the effectiveness of CSA interventions, farmers were asked to evaluate each intervention's usefulness across four dimensions: productivity, income, resilience, and input- use efficiency (specifically water and fertilizer use) as a proxy for mitigation (FAO, 2013; Khatri-Chhetri et al., 2019; Singh et al., 2021). Based on these four pillars, the farmers were initially asked to rank them according to their perceptions, and using those rankings, weights were created using the rank-sum weight method. Then, effectiveness was measured in terms of the percentage increase for each pillar by adopting the interventions. Productivity was measured by calculating the increment in yield per acre after adopting the intervention, and income was defined as the additional return from adoption. Resilience was proxied by the extent to which an intervention helped sustain livelihoods during climatic hazards (like floods or droughts). Input-use efficiency potential was assessed using indicators such as improvements in fertilizer and water use efficiency, which directly relate to reduced greenhouse gas emissions, indicating mitigation. Finally, with these ranks and valued effectiveness, a CSA effectiveness index (CSA-EI) was developed, acknowledging that not all interventions impacted every dimension equally.

$$\text{CSA} - \text{EI} = w_1 * \text{Productivity} + w_2 * \text{Income} + w_3 * \text{Resilience} + w_4 * \text{Mitigation}$$

where w_1 , w_2 , w_3 , and w_4 are weights identified for the four pillars, based on farmers' responses through the rank-sum weight method, and pillars measured by percentage.

Measuring upscaling potential of CSA interventions

The scalability of selected CSA interventions was assessed using upscaling potential that is determined by indicators such as technical feasibility, cost of technology, gender inclusivity, and synergy with government plans. These indicators are evaluated and prioritized for measuring upscaling potential by Khatri-Chhetri et al. (2019). A 5-point Likert scale was used to evaluate the importance of each indicator, where 0 = not relevant, 1 =very low importance, 2 = low importance, 3 = medium importance, 4 =high importance, and 5 = very high importance. Similar to CSA-EI indicator weighting, these four indicators of upscaling potential were given weights based on the rank given by farmers. The composite index on CSA upscaling potential (CSA-UP) was derived for each farm typology for the interventions they adopted. Technical feasibility, cost of implementation, inclusiveness, and sync with government plans were scored on a 1- 5 point scale based on farmers' perception alone for each CSA intervention.

$$\text{CSA} - \text{UP} = \beta_1 * \text{Technical feasibility} + \beta_2 * \text{Cost of technology} + \beta_3 * \text{Gender inclusivity} + \beta_4 * \text{Sync with govt. plans}$$

Where β_1 , β_2 , β_3 , and β_4 are weights estimated.

RESULTS AND DISCUSSION

Socio-economic and resource profiling of farm households

Table 4. gives the socio-economic and resource profile of farmers interviewed. Results reveal that the majority of the household heads are male, with an average age of 59 years and extensive average farming experience (37 years). Household sizes average four members, indicating moderate family labor availability. Ownership of farm machinery and implements shows significant variation, reflecting disparities in mechanization capacity. Social participation is strong, with active involvement in community initiatives, suggesting good potential for collective action and resource management.

The average farm size is 2.96 acres, with 44.5% being marginal farmers and a substantial proportion of small farmers, indicating limited land availability, a key factor influencing the choice of low-cost, efficient drought-resilient technologies. Credit access and crop insurance coverage suggest financial mechanisms are in place to support adopting risk management interventions, though gaps remain. Education levels vary, with nearly half of the farmers having completed high school, providing a reasonable foundation for understanding and implementing modern agricultural practices. The moderate proportion of irrigated land offers scope for water-efficient technologies, while livestock ownership enhances livelihood diversification, which can buffer drought impacts. Overall, the data reflect a farming community with a mix of constraints and enabling factors, where targeted interventions personalized to resource endowments and risk profiles can maximize the effectiveness of drought-mitigating agricultural interventions.

Table 4. Characteristics of farm households

Particulars	Variables	Mean/Frequency	Standard deviation
General	Age (years)	59	12
	Gender-male (%)	85.6	-
	Farming experience (years)	37	14
	Household size (no.)	4	2
Education status	Illiterate (%)	2.1	-
	Up to primary level (%)	41.1	-
	High school (%)	45.2	-
	More than higher secondary (%)	11.6	-
Farmer categorization	Marginal farmers (<2.5 ac)	44.5	-
	Small farmer (2.5-5 ac)	36.3	-
	Medium farmer (5-10 ac)	8.9	-
	Large (>10 ac)	1.4	-
Natural assets	Farm machinery and implements (000'Rs)	30.5	48.3
	No. of communication devices	3	1
	No. of conveyance units	2	1
Social assets	Social participation (%)	89.6	-
	Participation in community initiatives (%)	63	-
	No. of accessible common facilities	2	1
Natural assets	Farm size (acre)	2.96	2.4
	Gross cultivated area (acre)	4.15	2.65
	Gross irrigated area (acre)	3.19	2.38
	Livestock holding units	2	3
Financial capital	Annual crop income (000'Rs)	240.7	259.1
	Annual livestock income (000'Rs)	206.4	223.6
	Non-farm income (000' Rs)	138.4	168.9
	Credit taken (%)	76.7	-
	Crop insurance (%)	46.6	-
Total number of respondents		146	

Source: Authors estimation

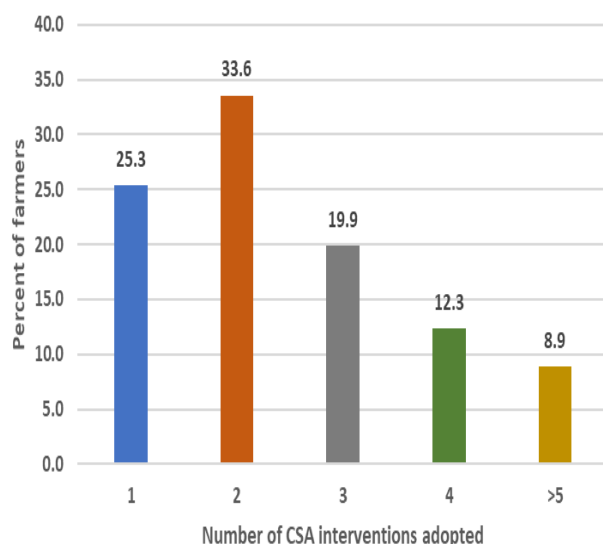
Adoption of CSA interventions

The farmers have adopted a diverse range of CSA interventions to mitigate drought stress, enhance productivity, and improve resource-use efficiency (Table 2). Water management interventions include micro-irrigation in coffee plantations, construction of percolation pits, and various water storage and harvesting structures to optimize water availability during dry spells. In crop management, stress-tolerant and drought-resilient varieties such as cowpea (VBN3) have been promoted, along with summer cropping in rice fallows (sesame) to utilize residual soil moisture and improve diversification by optimizing land use. Mechanization support through a custom hiring center and demonstration of drone technology has improved operational efficiency. Livestock productivity is supported by mineral mixture supplementation. Collectively, these technologies address the critical challenges of water scarcity, climate variability, and farm profitability in the region. This also supported the integrative approach of farmers in adopting traditional and innovative CSA interventions suitable to the locale based on their preferences (CIAT, 2014).

The adoption pattern of CSA interventions reveals a moderate level of diversification among farmers (Figure 3). A significant proportion of farmers (33.6%) have adopted two interventions, followed by 25.3% adopting one, indicating that while adoption of interventions is common, inclusive adoption across multiple categories remains limited. Only 8.9%

of farmers have integrated more than five interventions, reflecting a smaller group of highly adaptive and resourceful farmers. In terms of category-specific adoption, 34.2% of farmers depend on interventions supporting mechanization of the farms, either through custom hiring centres or by utilizing the services of drones for fertilizer applications. These interventions suggest a strong inclination of farmers towards services or interventions that reduce the cost of farm operations or ease of operations by enhancing labor efficiency and improving resource usage. Water management is the second most adopted intervention (29.5%), underlining the importance of addressing water scarcity in the region. Crop management innovations follow at 22.6%, while livestock-related interventions are the least adopted (13.7%), possibly due to resource constraints or lower perceived returns. A vast proportion of farmers used different interventions in combination that can substantially reduce the drought impact on their farm income and livelihood (Khatri-Chhetri et al., 2017). This highlights a gradual but uneven adoption of different interventions, with mechanization and water management emerging as the most preferred, based on the major crops cultivated and due to water scarcity (Easterling et al., 2007).

Adoption intensity of CSA interventions



Adoption diversity among CSA interventions

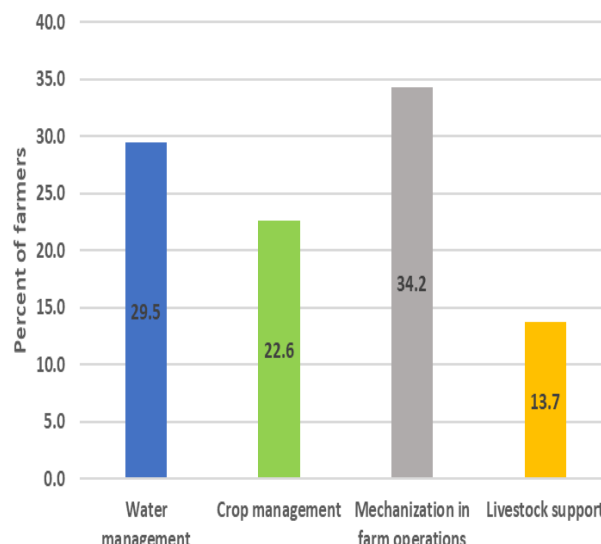


Figure 3. Adoption pattern of agricultural technologies

Farm household typology construction

The PCA conducted on key variables of the study area yielded 13 components (Table 3), of which the first four emerged as the most influential in explaining the variability within the dataset (Table 5). This is based on eigenvalues greater than or equal to 1. Component 1 accounts for 33% of the total variance. Similarly, component 2, component 3, and component 4 contribute 23%, 16%, and 8% of the variance, respectively. This indicates that a substantial portion of differences among farmers is explained by factors such as land possessed, gross cropped area, gross irrigated area, crop income, and livestock income. Together bringing the cumulative variance explained by the first four components to 80%.

Table 5. PCA result output

Component	Eigenvalue	Proportion	Cumulative
Comp1	4.29	0.33	0.33
Comp2	2.96	0.23	0.56
Comp3	2.12	0.16	0.72
Comp4	1	0.08	0.80
Comp5	0.86	0.07	0.86
Comp6	0.63	0.05	0.91
Comp7	0.39	0.03	0.94
Comp8	0.37	0.03	0.97
Comp9	0.15	0.01	0.98
Comp10	0.14	0.01	0.99
Comp11	0.07	0.01	1
Comp12	0.02	0	1
Comp13	0.01	0	1

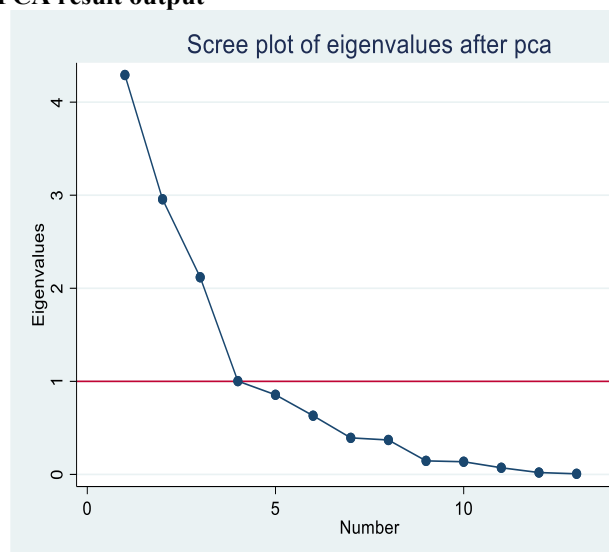


Figure 3. Scree plot of PCA result

Source: Authors estimation

It is also represented through a scree plot (Figure 3), and factors that create variance have factor loadings above 0.3, based on this, the cluster was formed (Table 6). This high cumulative variance demonstrates that these components effectively summarize the majority of variability in farmer characteristics, making them highly suitable for subsequent clustering. These PCA results provide a robust foundation for the subsequent cluster analysis, enabling the formation of distinct farm typologies that capture the heterogeneity in resource endowments, which can influence the adoption of different CSA interventions in the study area.

Table 6. PCA loadings for the first four principal components(PCs), indicating the contribution of each variable through PCs for clustering the households.

Variables	Comp 1	Comp 2	Comp 3	Comp 4	Unexplained
Age	-0.02	0.08	0.23	0.90	0.06
Household size	-0.03	0.55	0.06	-0.05	0.08
Land possessed (acre)	0.46	0.02	0.06	-0.08	0.08
Gross cropped (acre)	0.43	0.03	0.11	-0.07	0.16
Gross irrigated (acre)	0.41	0.07	0.09	-0.07	0.25
Livestock units	-0.13	-0.04	0.58	-0.25	0.15
Farm machinery and implements ('000Rs)	0.40	0.01	0.04	-0.02	0.29
Crop income ('000Rs)	0.44	0.00	-0.05	0.02	0.17
Livestock income ('000Rs)	-0.15	-0.04	0.61	-0.21	0.08
Non-farm income ('000Rs)	-0.11	0.31	-0.41	-0.14	0.28
Family expense ('000Rs)	-0.02	0.55	0.09	-0.08	0.08
No. conveyance units	0.12	0.33	0.20	0.19	0.49
No. communication devices	-0.11	0.41	-0.01	-0.08	0.45

Source: Authors estimation

The principal component (PC) scores obtained from the PCA were used as the input dataset for cluster analysis to classify farmers into distinct farm typologies. A two-step clustering approach was adopted. First, hierarchical clustering was performed using Ward's method, which begins with each farmer as an individual cluster and successively merges the most similar clusters based on minimum within-cluster variance. This agglomerative nesting process was visualized through a dendrogram (Figure 4), providing a clear depiction of the merging sequence and similarity levels. The optimal number of clusters was determined by examining the maximum average silhouette width for different k-means clustering solutions, ensuring the selection of a grouping structure with the best internal cohesion and separation. Based on this criterion, the dendrogram was cut to yield four distinct farm types (Table 7), each representing farmers with relatively homogeneous resource endowments, management practices, and CSA adoption patterns within the study area. This typology forms the foundation for subsequent analysis of the effectiveness and scalability of interventions.

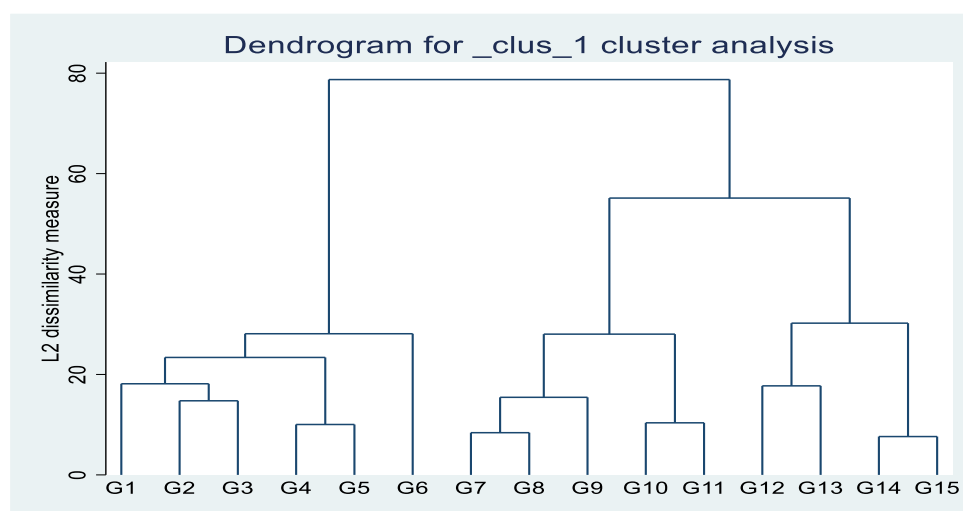


Figure 4. Cluster dendrogram

Bartlett's test checks if the observed correlation matrix diverges significantly from the identity matrix. Further, the KMO criterion confirms that the factor analysis is appropriate for the sample. The value of KMO for the analysis was 0.68, which is regarded as acceptable, and Bartlett's test was significant, validating the PCA analysis.

The four farm typologies derived from clustering exhibit distinct structural and functional characteristics (Crowley and Carter, 2000) that highlight the farm diversity (Table 8) shaping the adoption of different interventions. Cluster 1 represents relatively resource-rich farmers, with the largest average landholdings, highest investment in farm machinery, and thus generate substantial crop income. Abundance of resources motivates them to adopt more interventions that require high capital, like micro-irrigation and use of machinery. Cluster 2 is characterized by larger household sizes, moderate landholding and irrigated land, and diversified income sources, including significant non-farm earnings.

Livestock holdings and livestock income are also important in this group. Based on their diversity in farming, these farmers adopted interventions from all categories based on their farm needs. Cluster 3 comprises resource-constrained farmers with the smallest landholdings and lowest crop income. These marginal crop farmers aim to improve their farm productivity, crop diversity, and maximize land utilization through drought-tolerant crops, which makes them more inclined towards crop management interventions. Cluster 4 stands out for its high livestock orientation, with the largest herd size and dominant livestock income, despite limited land resources and low crop income. This group has minimal non-farm earnings and relies heavily on animal husbandry as the primary livelihood source, thus focusing on livestock support interventions. The magnitude of most of the 13 livelihood assets was significantly different across the 4 cluster types, underlining the need for such clustering, and the resulting cluster types were named (Table 7). Various farm typology studies helped in exploring typology-based opportunities to focus more on the efficiency and constraints in adoption patterns (Kuivanen et al., 2016; Kumar et al., 2019). We thus explore the effectiveness and upscaling potential of adopted CSA interventions based on farm typology. Further, the Kruskal-Wallis test was applied to evaluate differences among variables across the identified farm typologies, ensuring robust cluster validation to measure effectiveness (χ^2 value = 37.16, p-value = 0.02) and scalability (χ^2 value = 9.89, p-value = 0.00). The significant value of the Kruskal-Wallis test indicates that the 4 clusters differ significantly.

Table 7. Cluster details

Clusters	Farm typology	Number of farmers	Major CSA interventions adopted (no. of farmers)
1	Resource-intensive crop farmers	59	Water management (35) Mechanization in farm operations (20) Crop management (4)
2	Diversified household-oriented farmers	47	Mechanization in farm operations (26) Water management (8) Crop management (8) Livestock support (5)
3	Marginal crop farmers	24	Crop management (20) Mechanization in farm operations (4)
4	Livestock-oriented farmers	16	Livestock support (15) Crop management (1)

Table 8. Structural and functional characteristics of households under different clusters.

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Age	56	63	56	61
Household size	3	6	4	4
Land possessed (acre)	4.46	2.39	0.98	1.76
Gross cropped (acre)	5.74	3.62	1.56	2.82
Gross irrigated (acre)	4.53	3.01	1	1.67
Livestock units	1	2	2	8
Farm machinery and implements ('000Rs)	56.1	16.7	4.5	12.4
Crop income ('000Rs)	432.7	162.3	43.3	51.7
Livestock income ('000Rs)	116.7	155.7	223.3	648
Non-farm income ('000Rs)	79.5	254.8	141.8	20.9
Family expense ('000Rs)	267	461.1	294.9	294
No. conveyance units	2	2	1	2
No. communication devices	3	4	3	3

Source: Authors estimation

Effectiveness of CSA interventions across farm typology

Among the four indicators, farmers have given maximum weightage to resilience (0.31), followed by productivity (0.29), income (0.28), and input use efficiency (0.12). Apart from income and productivity, farmers indicated that resilience against drought is critical to overcoming natural shocks by reducing poverty and enhancing agricultural sustainability (Kumar et al., 2020). However, crop productivity and income remain equally important as they are intertwined, thus allowing farmers to measure them equally. The effectiveness of the adopted CSA interventions by four farm typologies in the drought-prone region is given in Table 9.

Across the four indicators of CSA effectiveness, resource-intensive crop farmers and livestock-oriented farmers have perceived resilience as the major effective indicator, while diversified household-oriented farmers and marginal crop farmers identified input use efficiency and income as the major domains with high effectiveness, respectively. This indicates that resource-intensive farmers can leverage capital-intensive adaptations like micro-irrigation and water harvesting to better withstand climatic stresses while managing to use machinery and inputs efficiently. The diversified household-oriented farmers report that their mixed-cropping and household-focused strategies allow them to optimize

resource utilization, even though overall production and monetary returns remain average. Marginal crop-dependent farmers stand out for achieving the highest scores in both productivity and income. This suggests that CSA interventions help them achieve additional and substantial livelihood gains. However, their resilience score is lower, indicating their potential vulnerability to shocks despite economic gains. The livestock-oriented farmers' score indicates that adoption of mineral mixture cattle feed did not improve much on any indicators compared to other typologies. This is possibly due to scale effects, market dependencies, or mismatch between the adoption intervention and their production systems. Considering previous studies, farmers perceive crop income and productivity to be the major indicators, as they focus on immediate effects (Khatri- Chhetri et al., 2019; Das et al., 2022). In contrast, our study depicts that farmers perceive resilience to recurrent shocks as the most prioritized indicator over others, considering that they prefer long-term gain and sustainability of farming over short-term improvements. Hence, providing additional incentives for CSA interventions for resilience and mitigation benefits can be strategized for the promotion and adoption of CSA interventions (Branca et al., 2021).

Comparing across the farm typologies, based on farmers' perception of the four pillars of CSA effectiveness, resource-intensive crop farmers perceived that CSA interventions are more effective in sustaining themselves in drought-prone regions. However, the differences in effectiveness suggest the need for typology-specific CSA interventions emphasizing resilience and efficiency for livestock-focused clusters and enhancing productivity for diversified and crop-oriented farmers. While micro-irrigation and construction of water harvesting structures on-site bear high initial costs and management intensity, making them more desirable for resource-intensive farmers, poor farmers rely on cost-effective interventions like crop management (Senyolo et al., 2018). This indicates that farmers prioritize interventions considering their socio-economic situations (Das et al., 2022). Thus, heterogeneity among farmers should be addressed before implementing interventions for their synergistic effects across farm typologies.

Table 9. Effectiveness of CSA interventions as perceived by the farmers

Sl. no	Typology	Mean score of effectiveness indicators				CSA-EI
		Productivity	Income	Resilience	Input-use efficiency	
1	Resource-intensive crop farmers	21.45 (-12.3)	22.9 (-15)	41.17 (-15.2)	35.41 (-22)	29.58 (-7.1)
2	Diversified household-oriented farmers	20.2 (-13.9)	20.57 (-16.5)	30.33 (-11.5)	48.87 (-31.9)	20.2 (-9.87)
3	Marginal crop farmers	35.33 (-22.4)	36.67 (-27.8)	26.83 (-5)	2.81 (-11.3)	22.71 (-14.1)
4	Livestock-oriented farmers	10.94 (-14.8)	13.75 (-15.3)	26.63 (-4.5)	-	15.53 (-11.1)

Note: Figures in parentheses denote standard deviation

Source: Authors estimation

Upscaling potential of CSA interventions across farm typology

For assessing the scalability of CSA interventions, the farmers of Padichira were given the highest weightage for technical feasibility (0.50), followed by cost of technology (0.31), gender inclusivity (0.13), and sync with government plans (0.06). The analysis of the CSA upscaling potential across farm typologies reveals clear differences in how various farm typologies perceive the scalability of CSA interventions (Table 10). All farm typologies except marginal crop farmers identified the cost of technology as the most important factor to upscale an intervention. Marginal crop farmers indicated technical feasibility as the major barrier to upscaling the interventions. Studies also demarcated the importance of the cost of technology and technical feasibility in influencing the upscaling potential of CSA interventions (Khatri- Chhetri et al., 2019). Though smallholder farmers prefer continuous financial support to continue CSA practices through government schemes (Tanti et al., 2022), our study reiterates the need for locale-specific interventions that are technically feasible and affordable for farmers to continue their practice (Autio et al., 2021). Among livestock farmers, they preferred gender inclusivity along with the cost of technology in improving scalability. This gender dimension being more pronounced in livestock management is mostly due to higher engagement of females in livestock management (Aryal et al., 2020; Das et al., 2022).

Among all 4 clusters, the marginal crop farmers stand out for recording the highest overall CSA-upscaling potential. This is largely driven by relatively strong perceptions of gender inclusivity and cost suitability, although their technical feasibility score is moderate. Interestingly, their low rating for alignment with government plans suggests that their high scalability perception is more farmer-driven rather than dependent on institutional frameworks. Low-income farmers prefer more on-site-specific integrated crop management (Khatri- Chhetri et al., 2017), and they see the potential of scalability. Next to them, the livestock-oriented farmers show a high overall scalability. The mean score of scalability indicators for this group indicates that while they see the interventions as affordable and inclusive, they perceive limitations in practical application and institutional backing. With these comparisons, the results underscore the need for tailored strategies that address the differing priorities of each typology, strengthening institutional alignment for livestock farmers and improving inclusivity for crop-oriented farmers to unlock full upscaling potential.

Thus, it suggests that categorizing households into farm typologies is beneficial to better target CSA interventions but also to understand how the specific intervention is effective and how to upscale based on different household types and their resource allocation (Zingore et al., 2007; Riveiro et al., 2013).

Table 10. Upscaling potential of agricultural technologies as perceived by the farmers

Sl. no	Typology	Mean score of upscaling potential indicators				CSA-UP
		Technical feasibility	Cost of technology	Gender inclusivity	Sync with government plans	
1	Resource-intensive crop farmers	4 (-0.9)	4.14 (-0.7)	1.82 (-0.9)	3.6 (-1.0)	49.5 (-9.0)
2	Diversified household-oriented farmers	3.79 (-1)	4.11 (-0.8)	2.19 (-1.4)	3.38 (-1.3)	57.89 (-6.0)
3	Marginal crop farmers	4.04 (-0.9)	3.67 (-0.8)	3.88 (-1.2)	2.25 (-1.0)	73.29 (-8.5)
4	Livestock-oriented farmers	2.94 (-0.8)	4.69 (-0.5)	4.13 (-0.6)	1.81 (-0.8)	70.05 (-9.2)

Note: Figures in parentheses denote standard deviation

Source: Authors estimation

CONCLUSION

Farm typology-based climate-smart agricultural interventions specific to a location were absent in most climate studies. This study distinctly looks at the farm typology-based effectiveness and upscaling potential of CSA interventions. Based on a participatory study of farmers in a drought-prone region of Wayanad, Padichira village, where NICRA projects were implemented in the past, the perceived effect and scalability were analysed. Socio-economic analysis of farmers revealed considerable diversity among farmers in terms of resource availability, landholding size, income composition, and access to infrastructure. Using principal component analysis and hierarchical clustering, farmers were grouped into four distinct typologies: resource-intensive crop farmers, diversified household-oriented farmers, marginal crop farmers, and livestock-oriented farmers. These typologies highlighted structural and functional heterogeneity, ranging from large, crop-focused systems with higher mechanization to small-scale, livestock-dependent systems with limited resources.

Across the typologies, the interventions adopted by farmers differed, as resource-intensive farmers focused more on water management and mechanization, while resource-poor crop farmers focused on strategies for crop management. Among these typologies, cluster 2 typology only incorporated the different categories of interventions. The farmers also indicated that they prioritize resilience as the most important indicator among the four (productivity, income, resilience, and input-use efficiency), considering they are affected by recurrent climate shocks. However, effectiveness assessment, based on four indicators, showed that resource-intensive crop farmers achieved the highest effectiveness index (CSA-EI), while diversified household-oriented farmers showed lower EI, though they demonstrated strong performance in input use efficiency. Similarly, farmers identified the cost of technology and technical feasibility as the main indicators to upscale any interventions. Across typologies, upscaling potential analysis indicated that marginal crop farmers and livestock-oriented farmers exhibited the greatest scalability, driven by technical feasibility, cost-effectiveness, and gender inclusivity, although factors like sync with government plans did not show much importance to farmers.

Overall, the findings underline that farm typologies are crucial for targeting interventions, as technology benefits and scalability vary widely across farmer groups. Tailored strategies should focus on leveraging the strengths of resource-rich and diversified systems for scaling, while enhancing resource access and institutional support for marginal and specialized systems. The combined methodological approach of socio-economic analysis, PCA-cluster-based typology, and effectiveness and scalability evaluation provides a robust framework for prioritizing and upscaling CSA interventions in drought-prone and resource-variable regions.

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