Environmental and Sustainability Indicators 27 (2025) 100847

Contents lists available at ScienceDirect

Environmental and Sustainability Indicators

journal homepage: www.sciencedirect.com/journal/environmental-and-sustainability-indicators

Tailored framework for sustainable intensification of marginal and small farms using farm typology to strengthen farm income

A.K. Prusty [a,*], N. Ravisankar [a,**], Jashanjot Kaur [b], Himanshu Joshi [c], Meenu Rani [a], Santiago Lopez Ridaura [d], Jeroen C.J. Groot [e], M.L. Jat [d,f], Luis Barba-Escoto [d,g], M. Shamim [a], M.A. Ansari [a], V. Paramesha [h], Kadambot H.M. Siddique [i], Poonam Kashyap [a], Raghuveer Singh [a], K.J. Raghavendra [a], T.P. Swarnam [a], A.S. Panwar [a], Sunil Kumar [a]

[a] ICAR-Indian Institute of Farming Systems Research, Modipuram, Meerut, 250110, UP, India
[b] Punjab Agricultural University, Ludhiana, India
[c] G. B. Pant National Institute of Himalayan Environment, Kosi-Katarmal, Almora, 263643, Uttarakhand, India
[d] International Maize and Wheat Improvement Center (CIMMYT), Mexico
[e] Farming Systems Ecology (FSE) -Wageningen University and Research, Wageningen, the Netherlands
[f] The International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Patancheru, 502324, Telangana, India
[g] Conservation Ecology Group, Groningen Institute for Evolutionary Life Science (GELIFES), University of Groningen, Groningen, the Netherlands
[h] ICAR-Central Coastal Agricultural Research Institute, Old Goa, Goa, 403402, India
[i] The UWA Institute of Agriculture, The University of Western Australia, Perth, WA 6001, Australia

ARTICLE INFO

Keywords:
Small farms
farm typology
multivariate analysis
Alternate farming systems
farm income

ABSTRACT

Farm typology studies assist in understanding how different farming components interact with each other and with the surroundings. These are often a prerequisite before devising adaptations to numerous agri-related challenges and in the development of sustainable agriculture policies. This holds importance for countries where the majority of the workforce is engaged in the agri-sector. The deliberated study investigates the determining factors that characterize the small and marginal farms spread across 16 states of India through typology to understand the limitations and challenges to formulate an alternative framework for leveraging their livelihood through enhanced income. The study clusters the surveyed farms under 06 farm types following a multivariate statistical approach. Further, it recommends alternate farming system models developed at research stations for different agro-climatic zones and the attributes of the respective farm type for the contemplated agro-climate zones. The study further scopes for the increment in annual farm income following the adoption of the recommended models. The results underscore the potential impacts of recommended models on the farmer's livelihoods.

1. Introduction

India, the most populous country in the world, housing 17.7 % of the world's population (Pew Research Center USA, 2023), accounts for 23 % of the world's small farms (IIFSR, 2015). These small farm avenues provide employment to a sizable portion of the rural populace and constitute ~85 % of all farm types in the country (FAO, 2014), though their contribution to arable land is only 44 %. Typically, the small farms tend to be more diverse and labor-intensive and, therefore, provide more opportunities for livelihood when compared to their large-scale counterparts on a per unit land basis. This attribute is particularly important in the Indian context where the agri-sector provides occupation to ~42.6 % of the workforce (World Bank, 2020), and with ~70 % of the agri-workforce being confided by family labor (NSSO, 2014). Certainly, small farms in the country are the backbone of the agri-sector (FAO, 2019). Besides rural livelihood, small farms also contribute towards food security by producing a large fraction of Indian staples such as wheat, rice, pulses, etc., with farm output that exceeds 50 % (Dev, 2012). Additionally, these farm types also assist in managing local biodiversity and overall ecological balance (Pretty, 2008). Despite such

* Corresponding author.
** Corresponding author.
E-mail addresses: aasiana143@gmail.com, ashish.prusty@icar.org.in (A.K. Prusty), n.ravisankar@icar.org.in (N. Ravisankar).

https://doi.org/10.1016/j.indic.2025.100847
Received 11 February 2025; Received in revised form 25 July 2025; Accepted 8 August 2025
Available online 9 August 2025

importance, small farming systems face many bottlenecks and challenges that affect their productivity, economic viability, and sustainability. Land fragmentation, mostly due to population growth and inheritance laws, reduces the efficiencies, adaptabilities, and economies of scale of small farming systems (Nagdeve, 2013; Niranjan 2014). Further, these have (i) Limited access to irrigation facilities constricting their resilience and productivity, especially in drylands (Kumar et al., 2014), (ii) Finite access to institutional credits often forcing small landholders to rely upon high-interest informal sources, thus, limiting their investment in technology and agri-inputs, and (iii) Tethered market access due to meager infrastructure and volatility in prices often causing sales of the produce at very low prices (Sharma and Agarwal, 2018). Coupled with the impacts of climate change (CC) leading to extreme weather events and increased climatic variability has adversely affected small farms, causing crop failures, increased vulnerability, and ultimately loss of livelihood (Singh and Sinha, 2019). This scenario recommends undertaking studies on farm typologies, which can contribute towards the development of farming practices that are relatively resilient to fragmented land acreages, markets, and climate change impacts.

By understanding how different farming components interact with each other and with the surroundings, adaptations can be devised to mitigate the above-discussed challenges. In this pursuit, consolidating different farming systems in homogeneous groups is quintessential, and farm typology studies can prove quite effective in this course. For a country like India, which has different agro-climatic zones (characterized by unique combinations of climate, soil, and topography), often location-specific studies are required for CC adaptation and mitigation (Paramesh et al., 2022). This study seeks to answer how small and marginal farms across diverse agro-climatic zones in India can be systematically classified using farm typology to facilitate targeted interventions for sustainable intensification and livelihood enhancement. Farm typology involves recognizing commonalities and underlying characteristics among various farm types towards creating a meaningful classification for understanding the complexities inherent to respective farming systems and summarizing this diversity among farming systems (Teixeira et al., 2018). Farm typology approaches have gained widespread global relevance as tools to segment heterogeneous farming systems and tailor interventions. This method assists in tailoring (i) The development of targeted interventions (Hazell, 2005), (ii) Efficient resource allocation towards maximizing agri-productivity and sustainability such as support to access agri-inputs and market for small farms, etc. (World Bank, 2007), (iii) Development of region cum farm specific technologies/packages following zone specific research (FAO, 2014), and (iv) Support to economic planning and rural development. In the context of India, farm typology studies facilitated (i) Need identification of small-scale farmers and the creation of customizable agri-packages (ICAR, 2018), (ii) Addressing of socio-economic disparities via targeted support and interventions (NITI Aayog, 2015), (iii) Enabling development of precise policy measures via segmentation of farming community, (iv) CC adaptation via development of climate resilient agri-practices such as drought-resistant crops for rainfed regions, etc. (TERI India, 2019), and (v) Enhancing productivity as different farm types have different productivity levels and understanding these productivity differences efforts can be made towards improvement of the same for farms where it is relatively low (Rao, 2017). Nearly every major reform, such as the Green Revolution, National Mission on Sustainable Agriculture (NMSA), Pradhan Mantri Fasal Bima Yojana (PMFBY), etc., in the agricultural sector, is somehow related to the farm typology studies (Ministry of Agriculture, 2014; Shah et al., 2018). Various statistical methods, especially the multi-variate analysis like principal components, cluster analysis, MANOVA, heteroskedastic extended ordered probit modes, etc., have been utilized by numerous researchers for farm typology studies across the globe (Kostov and McErlean, 2006; Milán et al., 2006; Tittonell et al., 2010; Righi et al., 2011; Alvarez et al., 2018), with some researches implementing the same approach for small landholder in India but at a regional scale (Kaur et al., 2021; Innazent et al., 2022; Prusty et al., 2022). Internationally, studies have adopted both conceptual and data-driven methods to classify farms. For instance, Tittonell et al. (2010) developed a typology in East Africa to link livelihood diversity with soil fertility outcomes using Principal Component Analysis (PCA) and clustering, while Alvarez et al. (2018) proposed a hypothesis-based typology framework. In Latin America, Cortez-Arriola et al. (2016) used whole-farm modeling to evaluate sustainable intensification options in Mexican dairy systems. In Europe, Groot et al. (2012) employed multi-objective optimization tools to redesign diversified farming systems, while in Kenya and Vietnam, Timler et al. (2020) utilized the FarmDESIGN model to promote nutrition-sensitive agriculture using typology-driven simulations. Recent studies from Ethiopia (Eshetae et al., 2024) and Ghana (Eshetae et al., 2025) emphasized the value of domain-specific typologies and resource-based classifications to improve the targeting of interventions under climate-smart agriculture frameworks using factor analysis for mixed data (FAMD) methods integrating PCA with Hierarchical Cluster Analysis (HCA) or Multi Correspondence Analysis (MCA), respectively. In the Indian context, typology-based studies have also expanded across agro-climatic zones and have demonstrated the effectiveness of targeted farming interventions. Kaur et al. (2021) classified farms in the Indo-Gangetic Plains based on mechanization, income, and diversification levels using PCA + HCA, leading to income gains exceeding 100 % under tailored interventions. Similarly, Innazent et al. (2022) applied typology to integrated farming systems (IFS) in Kerala, identifying production constraints and guiding context-specific solutions. Prusty et al. (2022) introduced FarmDESIGN modeling to redesign marginal farms in western Uttar Pradesh, achieving improvements in soil health, income, and nutrition indicators by combining PCA-HCA-based typologies with the FarmDESIGN and P-MODE optimization tools to redesign marginal farms for better soil health, profitability, and nutritional output. Similarly, Sharma et al. (2025) implemented the PCA + HCA method for developing functional-structural typology in Punjab to direct market access, diversification, and support schemes. A comprehensive review by Huber et al. (2024) consolidates the policy relevance of typology studies, suggesting improved data use and methodological innovation.

While prior studies on farm typology have provided insights into regional farming characteristics, there is a notable gap in nationwide assessments that systematically classify farm types across India's diverse agro-climatic zones and holistically address the diversity of small and marginal farms. Most studies focus on single-state/district/regional-level classifications, often neglecting the systemic heterogeneity and policy relevance of a nationally representative typology, thus limiting their applicability to wider uptake, upscale, and induction in the national policy framework. The presented study bridges this gap by employing a large-scale, pan-India approach to farm typology development. Unlike previous efforts, which were largely localized, this study analyzes farm classifications across 16 states, integrating PCA and HCA to delineate distinct farm types. This current pan-India study builds upon the previous efforts by offering a comprehensive and spatially expansive typology framework. Unlike localized studies, this work captures national-level heterogeneity, offering actionable insights for central and state policy-makers. Moreover, it strengthens the methodological continuity with global typology literature while adapting it for scale and contextual specificity in India's smallholder systems. Further, it identifies the key determinants influencing farm classification and their respective agro-climatic and socio-economic characteristics, and goes beyond the classification by linking farm typologies with alternative IFS models developed by the All India Coordinated Research Project (AICRP) tailored to different agro-climatic regions. Additionally, it assesses the potential impact of proposed alternative farming models on farm income and sustainability to support informed policy-making for small farmholders. While existing studies and related national missions provide valuable insights, ongoing and detailed farm typology studies remain essential for addressing the complex and evolving challenges, such as the dynamics of agricultural practices that evolve over time, the development of better market linkages and value chains, farmer indebtedness, migration, rural employment, formulation of better policy decisions, etc. The deliberated study, thus, not only provides an in-depth typology framework but also proposes practical pathways for sustainable intensification and income diversification following the adoption of alternate farm models. Further, the study is explicitly linked with multiple national and international initiatives such as the National Mission on Agricultural Extension and Technology (NMATE), NMSA, Doubling Farmers Income (DFI) initiative, Green Credit Program (Sustainable agriculture-based Green Credit) of the Ministry of Environment, Forest, and Climate Change (MOEFCC), India's Nationally Determined Contribution 1 (Mission LiFE), and United Nations Sustainable Development Goals (SDGs), namely, SDG 2-Zero hunger (2.3 & 2.4) and 12-Responsible consumption and production (12.2, 12.3, 12.4 & 12.6), respectively.

2. Methodology

2.1. Data collection

The benchmark data for the presented study were accrued from 918 households (HHs) through a combination of structured surveys, key informant interviews, and focus group discussions under the AICRP on IFS. The survey instrument consisted of four major modules, namely, farm structure & resources, economic & market characteristics, farm

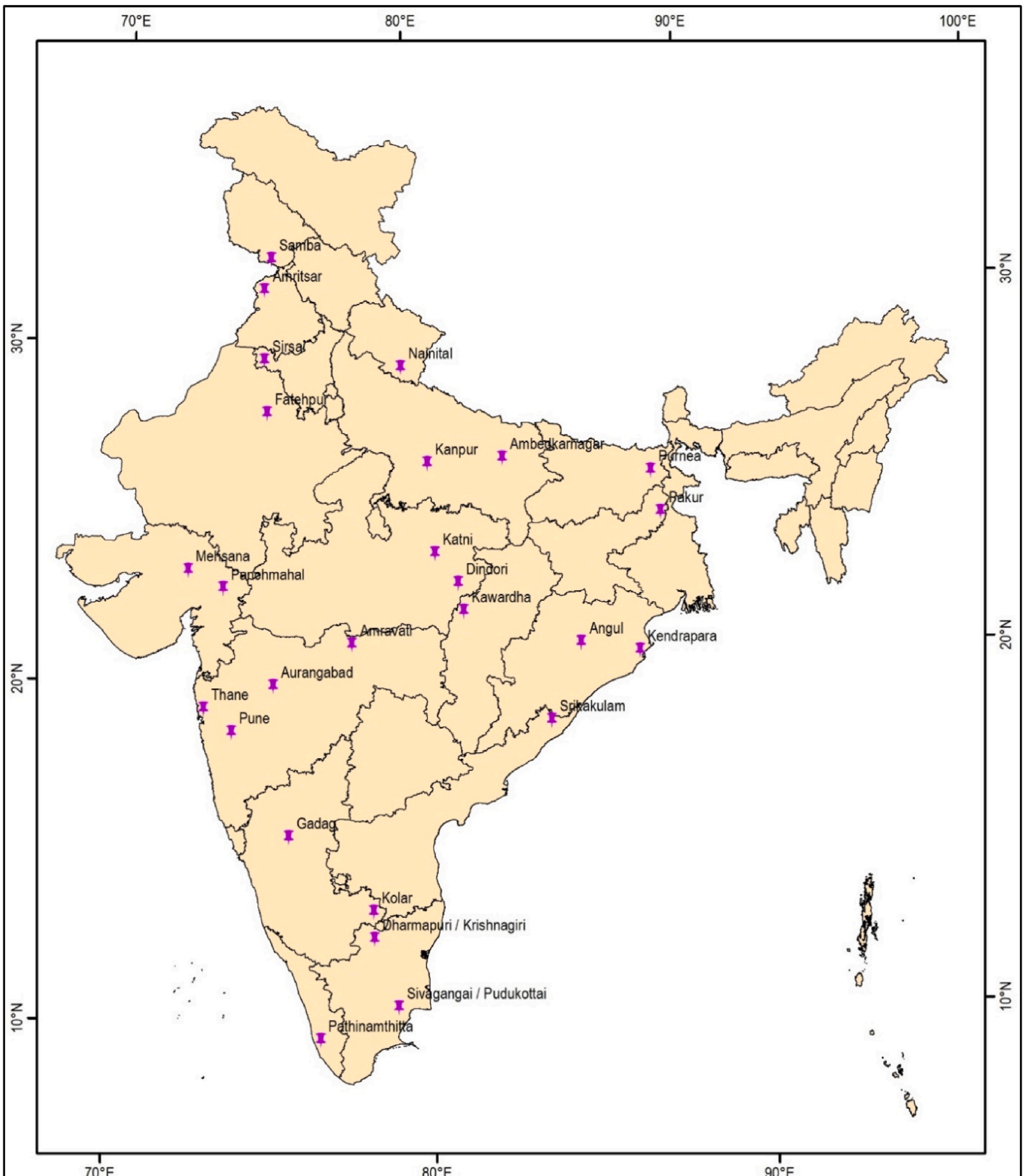

Fig. 1. Geographic index of surveyed locations across India.

management practices, perceived risks, and policy support. The study adopts a multi-stage stratified sampling approach to ensure representative coverage of diverse farm typologies across India's agro-climatic zones. The selected HHs were from 26 districts (administrative subunits of states/provinces), which were spread across 12 Agro-Climatic Zones (ACZ) in 16 states of the country, thus setting the scale of the study at the pan-India level. For the selection of HHs within the target district, all the blocks were classified into two categories based on their agricultural productivity, namely, low and high. The criterion for low and high productivity was derived from the average productivity of the target district. Following this classification, 02 blocks were selected from each of the target districts. From the identified blocks, 03 villages were selected from each, and for each village, 06 HHs were selected based on stratified random sampling among the class of small and marginal farmers. As a result, 36 HHs were selected from each district, leading to a total of 936 surveyed HHs. Following data cleansing to remove errors, outliers, and data entry inconsistencies, 918 HHs (98.08 %) were finalized for further data processing. The identified HHs were geo-tagged along with their agricultural parcels. If the agri-fields of an HH have a wider spatial distribution due to fragmented land holding, then geo-tagging of every location was also carried out since the managerial practices usually differ among the farming community for disjoint acreages. A structured questionnaire was used for the systematic characterization of existing farming systems among the HHs. This provided an understanding of their respective spatial dynamics and their inventory of elements influencing the productivity and profitability of the farming system under consideration. The questionnaire inquired over (i) General information such as family demographics such as age, land holding details, education status, family size, dietary preferences & patterns, household assets, etc., and (ii) Agricultural-related information such as level of farm mechanization, preferred crops, details of livestock, crop-wise inputs, overall production, market sales, self-consumption, overall income from various sects, HH-level expenditure, etc. Further, the surveys also attempted to apprehend women's involvement in the overall decision-making processes and discernment of various constraints concerning the existing farming systems. Fig. 1 depicts the index map for the sampled districts and their spread across the country.

2.2. Typology development

For the 918 HHs that were retained for the statistical analysis, 39 variables were extracted from the benchmark survey data. Of the 39 variables, 28 were retained for subsequent multivariate analysis. The reduction process was guided by both statistical prudence and domain relevance. First, seven individual livestock variables (number of cows, buffalo, calf, sheep, goat, pigs, and chicken) were consolidated into a composite indicator — the Total Livestock Unit (TLU) — which is widely recognized in typology literature as a more standardized and comparable measure of livestock holding across species (FAO, 2002). This approach minimizes redundancy and accounts for species-specific biomass and economic value. Second, two dietary preference variables (number of vegetarians and non-vegetarians in the household) were excluded due to limited variance and low explanatory value for farming system classification. Third, two demographic indicators (age and number of children) were also removed because their correlation with structural and economic variables was relatively weak, and they were not directly influential in defining farm resource use or production orientation. The retained 28 variables span four critical dimensions: structural (e.g., farm size, labor availability, TLU), cropping system (e.g., percent land under paddy, cereals, cash crops, etc.), productivity (e.g., crop yields, proportion of produce sold or consumed), and economic characteristics (e.g., income from crops, livestock, fisheries, and off-farm activities). This multi-dimensional framework provides a holistic and integrative representation of the farming systems and reflects their diversity in resource endowments, market orientation, and livelihood strategies. The final set of variables was also validated through consultations with subject matter experts (SMEs) from the AICRP-IFS program and national institutions. SME insights were critical in aligning the statistical structure with contextual realities, ensuring the typology framework reflects ground-level heterogeneity and supports policy-relevant classification and intervention design for small and marginal farm systems. The 28 variables were then categorized into the abovementioned four groups, namely, (i) Structural (04 N), (ii) Cropping system (06 N), (iii) Productivity (14 N), and (iv) Economic (04 N) indicators based on their role in defining farm typologies. Structural indicators (farm size, on & off-farm labor & total livestock unit (TLU)) define the physical and labor resources available to farms, playing a key role in their production capacity, efficiency, and operational scale. Farm size defines the extent of landholding, impacting production potential, labor (on-farm/off-farm) indicates subsistence farming, commercial scale & labor dependence of farms, and TLU quantifies livestock holding, assisting in distinguishing crop-only vs. mixed farming systems, thus, measuring farm diversification. Cropping system indicators (percent land under wheat, paddy, cereals, fodder crops, cash crops & other crops) provide insights into land use patterns, specialization, and diversification within farm typologies. The dominance of staple grains (paddy, wheat, cereals) reflects crop diversification, food security, and traditional agronomic practices, while the allocation of land to fodder crops signals livestock integration. Cash crop intensity differentiates farms based on their commercial orientation, and other crop intensity assist in capturing horticulture-based farms. These indicators help in identifying farm typologies based on their core cropping strategies, distinguishing cereal-dominant, cash crop, and other crops-based farms.

Productivity indicators measure farm productivity and market participation, distinguishing between subsistence-oriented and market-oriented farms. Yield indicators (paddy & wheat) indicate agronomic efficiency and productivity levels. The home consumption vs. sales provides crucial insights into commercialization trends and food security strategy, identifying whether farms operate primarily for self-sufficiency or for generating market surplus. Market integration indicators (percent sold vs. kept for home use) are particularly important for differentiating livestock sustaining & fodder surplus, small & high-income cash, and self-sustaining & commercial fruit/vegetable farms. Further, it also assists in understanding the value chain participation and economic sustainability of different farm types. Economic indicators (percent income from crops, livestock, fisheries & off-farm) are essential for understanding the financial sustainability, income diversity, and economic resilience of different farm types. Crop income reflects economic reliance on agricultural production, while livestock income measures the revenue generated from animal husbandry. Similarly, income from the fishery is included to account for farms integrating aquaculture (an emerging livelihood strategy in several regions), and off-farm income measures the extent of livelihood diversification beyond agriculture (relevant in regions where seasonal unemployment/climate risks push farmers to seek alternative income sources such as wage labor, business, or migration). Collectively, these indicators help differentiate subsistence, semi-commercial, and fully commercialized farm systems.

To avoid the effects of collinearity, the filtered 28 variables were then subjected to correlation analysis. The check for collinearity was made using the Variance Inflation Factor (VIF) based on the recommendations of Hill et al. (2011) and Montgomery et al. (2012) in Spyder Python v 5.4.3 in Anaconda Navigator 2.5.2 platform using NumPy, Pandas, SciPy, Matplotlib, and Seaborn libraries.

2.3. Multivariate analysis

The selected 28 parameters were subjected to multivariate analysis. Multivariate analysis is pivotal in farm typology studies as it allows to comprehensively categorize different farms by simultaneously considering multiple variables (Nakasujja et al., 2022; Wang et al., 2022; Khan et al., 2023). First, a dimension reduction technique, namely, PCA, was followed to identify the 21 most influential parameters (criteria variables) from the dataset. These criteria variables were then subjugated to HCA for grouping individual HHs/farm types into groups/clusters based on their attributes. Both the statistical methods were carried out in Python with scikit-learn and hierarchical-clustering libraries in addition to the earlier-mentioned packages.

2.3.1. Principal components analysis

To manage the high dimensionality of the dataset while retaining the maximum possible variance, a dimension reduction technique has to be applied to the dataset. Given the complexity of farm systems—which involve interrelated structural, economic, and production variables that are in interval and ratio scale—PCA is particularly suited as it identifies latent patterns without overfitting the data (Jolliffe, 2002). It also enables the transformation of correlated variables into uncorrelated Principal Components (PCs), making the data suitable for subsequent clustering (Rencher and Christensen, 2012). Prior typology studies have successfully used PCA to extract dominant features and structure on farm heterogeneity across varying agro-ecological and socio-economic settings (Kiptot et al., 2019; Mowo et al., 2020; Santos et al., 2020; Nguyen et al., 2022; Pedersen et al., 2021), supporting its utilization in this context. Further, it aids in data visualization by apprehending the relation between data points in lower dimensions (Abdi and Williams, 2010). Additionally, PCA assists in the identification of criteria variables among the dataset via variance explanation and respective loading scores of the input parameters (Rencher and Christensen, 2012). The PCs that have eigenvalues greater than 1 were classified as legitimate PCs. Only these were considered for the identification of 17 criteria variables from the 28 input parameters based on the sum of absolute values of loading scores of the respective parameters, though a few variables (04 N) were also added based on the consultations with the SMEs. This led to the downscaling from 28 input parameters to 21 (25 % reduction in input data) for the HCA.

2.3.2. Hierarchical Cluster Analysis

Several studies have demonstrated the usability of HCA in farm typology studies in regards to the identification of different farm types, understanding their diversity and pattern, in comparative analysis as well as in policy planning (Sraïri and Errahj, 2018; Carelsen et al., 2021). Using the 21 criteria variables, HCA was employed for the classification of farm types into distinct groups (clusters). For identification of the optimal number of clusters, two indices, namely, the silhouette score and Davies-Bouldin (DB) index, were computed. Typically, the optimal number of clusters has a higher silhouette score and lower DB index (Rousseeuw, 1987). For the presented study, a compounded index, which is the ratio of the silhouette score to the DB index, was estimated. The cluster that has the greatest value of this compounded index was chosen as the optimal number. The 918 HHs were then grouped under the identified optimal number of clusters, and suitable farm-type nomenclature was assigned to each cluster based on their respective descriptive stats. The cluster data was then subjected to the Kruskal-Wallis (KW) test to ascertain statistically significant differences among the identified clusters for the input parameters (Kaur et al., 2021) using the scipy.stats library in Python.

2.3.3. Potential biases and limitations of the chosen method

While the combination of PCA and HCA has been widely utilized in farm typology, the method is not without limitations. PCA is sensitive to variable scaling and assumes linear relationships among variables. Although standardization was applied to normalize the data, non-linear associations and interactions among variables may not be fully captured (Abdi and Williams, 2010). Additionally, PCA results can be influenced by outliers, which may skew the identification of principal components. While steps such as outlier removal and multicollinearity checks (using VIF) were undertaken, the possibility of residual distortions remains. Second, HCA relies on distance metrics (Euclidean in this case) and linkage methods that may impose artificial boundaries between farm types, particularly when data clusters are not clearly separable. The choice of the number of clusters—though supported by the ratio of silhouette and Davies–Bouldin indices—still involves a degree of subjectivity, which could influence typology outcomes (Ketchen and Shook, 1996). Further, the analysis is cross-sectional, based on data from a single point in time. This limits the ability to capture seasonal or temporal dynamics that could influence farm structure, income variability, or market access. Additionally, while efforts were made to include diverse agro-climatic zones and perform stratified sampling, the study may not fully capture regional subtleties, especially in districts with highly localized practices or socio-cultural variations. Moreover, while expert consultation informed the final selection of variables, this introduces a subjective dimension that, although grounded in experience, may still carry bias. Future research could explore the application of non-linear dimensionality reduction techniques (e.g., t-SNE or UMAP) and model-based clustering (e.g., Gaussian Mixture Models) to validate and potentially refine the typologies.

2.4. Development of farm types

The study further attempts to link the nomenclatured farm types (from the HCA) to the suitable IFS models, which were developed under the AICRP-IFS project towards improving sustainability chiefly in terms of farm productivity, nutritional security, and overall profitability. The AICRP on-station models were developed based on multi-location experimentation and farmer's participatory approach at different agro-climatic zones, soil types, and ecological conditions (ICAR, 2023). The HCA farm types were further examined with respect to specific ACZ, evaluating how each farm type is distributed. Following local adjustments, this formed the basis for recommendations. For almost each HCA farm type a proposition for an IFS model was made (based on the structural constituent of the HCA farm type to a similar IFS model) for the respective agro-climatic zone such that implementation of the suggested model shall deliver resource optimization, income diversification, economic viability, improved risk management, food security, climate adaptation, and overall environmental protection as well as sustainability.

3. Results

3.1. Profile of respondents

Analysis of benchmark survey data of 918 HHs across the country suggested that, on average, the typical farm size of an HH is 0.90 ± 0.02 ha with a range from 0.10 ha (marginal) to 6.0 ha (medium). Following the landholding classification of the Department of Agriculture, Cooperation & Farmers Welfare, GOI, 66.34 % of the respondents are in the category of marginal farmers, while 30.07 %, 3.38 %, and 0.21 % are in the class of small, semi-medium, and medium farmers, respectively. The average age of respondents is 46.49 ± 0.40 years with a range of 20–85 years, hence covering the entire spectrum of the working age group. Orientation of production among the contemplated HHs is diverse, which is evident from the allocation of land holdings to different crops such as rice, wheat, cereals, fodder, cash crops, etc. For a typical HH, 43.40 ± 1.35 % of the land is engaged in paddy cultivation, followed by wheat (26.66 ± 1.34 %), cereals (22.60 ± 1.67 %), and fodder crops (8.60 ± 0.72 %), respectively. Crops were not only raised for sale in the market but also for consumption at home. For major crops such as rice, wheat, cereals, and other cash crops, 36.99 ± 1.19 %, 27.44 ± 1.09 %, 11.37 ± 0.95 %, and 35.37 ± 1.36 % of the produce is kept for domestic use. On average, TLU for an HH is 3.00 ± 0.29 units. The primary income is majorly from crop cultivation (70.72 ± 1.11 %), followed by livestock (25.90 ± 0.78 %), and some off-farm work (3.90 ± 0.51 %). In regards to the distribution, following the recommended guidelines from Pallant (2021), of the considered 39 variables only 06 parameters, namely, A, WonF, WoffF, Ch, NV, and V, exhibited near-normal distribution due to their skewness values close to 0 suggesting approximate symmetry in the dataset. The other parameters are strongly positively skewed, while no variable showed attributes for negative skewness. Table 1 illustrates the descriptive stats for the 39 considered variables concerning the respondents.

3.2. PCA outputs and parameter selection for HCA

For the 28-input variable, a correlation matrix was developed, and respective VIF values were computed for each parameter to check for collinearity in the dataset. For all the input variables except percent income from crops (Cincome), the values VIF are between 1 and 5, indicating a moderate correlation with other variables. For Cincome, the VIF is 6.692, suggesting a high correlation with other variables, an indication of potential multicollinearity. Despite being a potential multicollinearity variable, Cincome was still taken for the PCA as it is one of the essential indices in the context of farm typology studies. Fig. 2 depicts the correlation plot and the VIF values of the 28 input variables.

Following the PCA, it was observed that 12 PCs have eigenvalues greater than 1 and, therefore, are considered as the legitimate PCs (Jackson, 1991). Cumulatively, these legitimate PCs explained 66.14 % variance in the dataset. 17 variables that load well in these legitimate PCs (having the largest absolute value in the sum of loading scores) were considered as criteria variables for the subsequent HCA. These include S, WonF, WoffF, Pint, Wint, CEint, fodint, Pyield, Rhome, Rsold, Wsold, CEhome, CEsold, CCsold, TLU, Cincome, and Lincome, respectively. Visualization of these variables can also be made from the biplot, which is presented in Fig. 3.

Additionally, four more parameters relating to the percentage of land under cash crop (Cashint) & other crops, including horticulture (othercropint), wheat yield (Wyield), and percent wheat kept for home (Whome), were also added as the criteria variables based on the exposition of the subject experts and published literature (Rehman et al., 2003; Verkaart et al., 2020). As a result, 21 criteria parameters were finalized for successive HCA. Fig. 4 illustrates the scree plot and the Cumulative variance explained by the PCs.

3.3. Outputs from HCA and farm types

The 21 criteria parameters were subjected to HCA in the Python environment. The input data is first standardized using the standard scaler such that the arithmetic mean becomes zero and the standard deviation becomes unity. Then the Euclidean distance between each pair of data points is computed. Initially, each of the individual points is considered a unique cluster, and at each step, two closest data points are merged to form another cluster until all data points belong to a single cluster, generating a tree-like structure called a dendrogram. The optimal number of clusters was determined by a compounded index, which is the ratio of the silhouette score and DB index (depicted in Fig. 5). For six clusters, the compounded index was found to be 0.058, the highest among all tested clusters, confirming that six clusters were the best fit. Based on cluster membership, each farm was assigned to one of six distinct farm typologies. The names of the six farm types were

Table 1
Descriptive stats of respondents for the accounted variables.

Parameter	Index	Mean ± SE	Range	Skewness	Kurtosis
Farm size (ha)	S	0.90 ± 0.02	5.90	2.50	16.09
Age (years)	A	46.49 ± 0.40	65.00	0.26	−0.36
Work on farm (N)	WonF	1.67 ± 0.04	9.00	2.56	7.66
Work off farm/Hired labor (N)	WoffF	2.34 ± 0.04	7.00	0.18	−0.18
No. of children in HH (N)	Ch	2.55 ± 0.04	8.00	0.38	0.83
Nov-vegetarian members in HH (N)	NV	2.62 ± 0.09	12.00	0.39	−0.97
Vegetarian members in HH (N)	V	2.31 ± 0.09	30.00	1.66	9.65
Percent land under paddy (%)	Pint	43.40 ± 1.35	160.00	0.23	−1.46
Percent land under wheat (%)	Wint	26.66 ± 1.34	500.00	3.00	22.50
Percent land under cereals (%)	CEint	22.60 ± 1.67	800.00	7.98	99.66
Percent land under fodder crops (%)	fodint	8.60 ± 0.72	250.00	4.03	24.24
Percent land under cash crops (%)	Cashint	39.09 ± 1.52	400.00	1.65	5.37
Percent land under other crops, including horticulture (%)	othercropint	10.53 ± 0.90	490.91	7.96	112.19
Paddy yield (kg/ha)	Pyield	2960.89 ± 70.97	12150.00	0.42	0.20
Wheat yield (kg/ha)	Wyield	2065.58 ± 80.14	31500.00	4.14	41.97
Percent rice kept for home (%)	Rhome	36.99 ± 1.19	100.00	0.50	−1.12
Percent rice sold (%)	Rsold	39.38 ± 1.21	100.00	0.29	−1.37
Percent wheat kept for home (%)	Whome	27.44 ± 1.09	100.00	1.00	−0.23
Percent wheat sold (%)	Wsold	34.45 ± 1.22	100.00	0.43	−1.40
Percent cereals kept for home (%)	CEhome	11.37 ± 0.95	200.00	2.60	6.63
Percent cereals sold (%)	CEsold	16.05 ± 1.11	100.00	1.87	1.81
Percent fodder crop kept for home (%)	fodHH	21.30 ± 1.14	100.00	1.20	−0.26
Percent fodder crop sold (%)	fodsold	16.48 ± 0.99	100.00	1.84	2.11
Percent cash crops kept for home (%)	CChome	35.37 ± 1.36	100.00	0.48	−1.56
Percent cash crops sold (%)	CCsold	12.31 ± 0.74	100.00	2.14	4.18
Percent other crops kept for home (%)	Othercropshome	7.47 ± 0.64	100.00	3.17	10.28
Percent other crops sold (%)	OCsold	25.53 ± 1.31	100.00	1.04	−0.75
No. of cows in HH (N)	Cow	0.94 ± 0.04	6.00	1.33	2.01
No. of buffalo in HH (N)	Buffalo	0.67 ± 0.04	15.00	3.61	27.02
No. of calf in HH (N)	Calf	1.45 ± 0.05	12.00	1.22	2.99
No. of sheep in HH (N)	Sheep	0.04 ± 0.02	8.00	12.74	175.71
No. of goat in HH (N)	Goat	0.89 ± 0.08	40.00	6.70	74.95
No. of pig in HH (N)	Pig	0.05 ± 0.01	4.00	7.42	64.94
No. of chicken in HH (N)	Chicken	7.55 ± 2.89	2000.00	17.66	345.69
TLU (N)	TLU	3.00 ± 0.29	202.80	16.80	324.15
Percent income from crops (%)	Cincome	70.72 ± 1.11	768.71	9.47	198.57
Percent income from livestock (%)	Lincome	25.90 ± 0.78	100.00	0.61	−0.58
Percent income from fishery (%)	FISHincome	0.27 ± 0.07	33.67	10.21	116.83
Percent income from off-farm work (%)	OFFincome	3.90 ± 0.51	100.00	3.95	14.50

SE: Standard Error, N: Number.

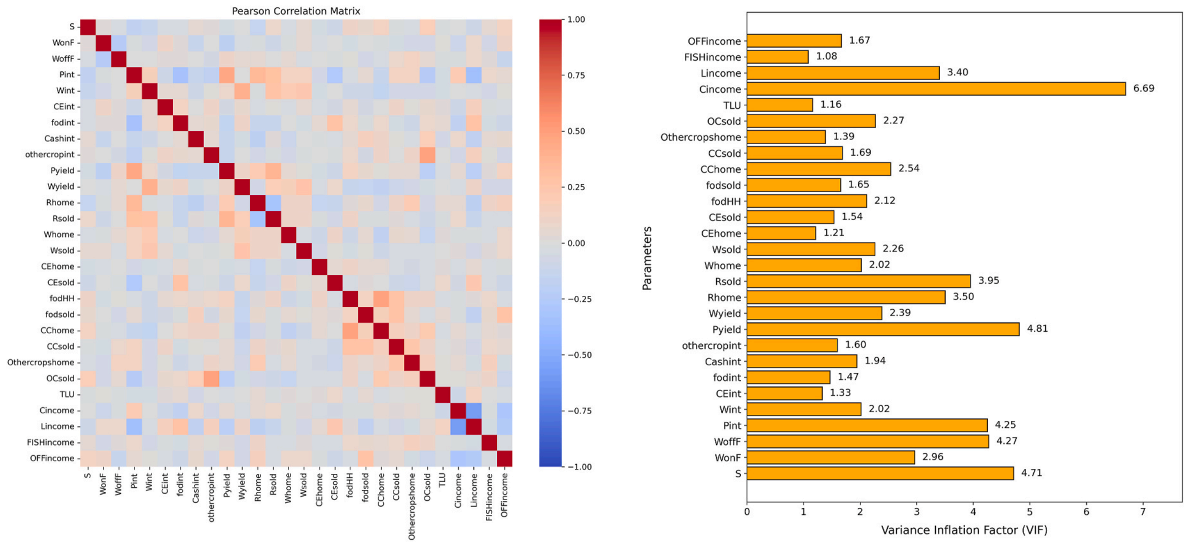

Fig. 2. Correlation plot and VIF bar charts for the PCA input parameters.

assigned based on the dominant farm characteristics in each cluster, derived from the average values of 39 input variables. The classification names were given based on average farm size, cropping system, livestock composition, income sources, and market participation. These are.

1. FT1 (Diversified marginal farmers with milch-poultry livestock) accounts for 11.33 % of the surveyed HHs, has an average landholding size of 0.84 ± 0.04 ha, and has the greatest number of hired labor (2.53 ± 0.12). This class exhibited the highest degree of crop diversification relative to other farm types, with a significant portion of the respective crop produce being sold. Further, it has an average livestock size of 2.21 ± 0.14 TLU, with cow, buffalo, goat, and chicken being the primary animals. A major contributor to their overall income is crops (65.05 ± 2.15 %), followed by livestock (33.69 ± 2.15 %). However, a trivial portion of their income comes from off-farm work (1.28 ± 0.90 %).
2. FT2 (Marginal paddy-wheat cultivating farmers with dairy-poultry-fishery and diverse income) contributes to 56.10 % of the contemplated HHs and has an average farm size of 0.87 ± 0.02 ha. This category has the largest paddy yield (3892.48 ± 76.64 kg/ha) and rice stock for domestic consumption (53.00 ± 1.45 %). Additionally, this class holds the greatest proportion of cash crops being sold to the market (16.34 ± 1.13 %) and has an average livestock size of 2.51 ± 0.10 TLU. In regard to overall income, crops (77.70 ± 1.70 %) hold the largest share, followed by livestock (17.28 ± 0.88 %). Moreover, this class has the largest revenue from off-farm activities and fish cultivation in comparison to other farm types, which is 5.88 ± 0.82 % and 0.47 ± 0.13 %, respectively.
3. FT3 (Small farmers with wheat-dominated cropping and milch-goatery livestock), which comprises 8.88 % of the surveyed HHs, has the largest land holding (1.11 ± 0.11 ha), thus placing them in the category of small farmers. This category has the lowest average age of the producers (45.33 ± 1.31 years) and the largest percentage of their land under wheat cultivation (69.72 ± 3.98 %) and cereals (53.71 ± 14.60 %), as well as the highest wheat yield (4468.30 ± 481.78 kg/ha). The average livestock size of this farm type is 2.50 ± 0.15 TLU, which majorly comprised of milch animals like buffalo. Its income is primarily from crops and livestock, which account for 58.12 ± 2.27 % and 41.61 ± 2.26 % of the overall income.
4. FT4 (Marginal farmers with paddy-wheat cropping system and dairy cattle) has an average landholding of 0.83 ± 0.04 ha and contributes to 11.00 % of the sampled HHs. These are largely paddy and wheat cultivators and sold the greatest portion of the cereal produce to the market (92.70 ± 2.14 %). This farm type has the least livestock size of 2.15 ± 0.17 TLU mainly consisting of dairy animals such as cows and buffalo. Crop and livestock sources contribute 56.49 ± 2.33 % and 42.14 ± 2.38 % to the total income of this farm type, respectively.
5. FT5 (Cereal and cash crop producing Marginal farmers with milch-goatery-poultry and some off-farm income) with an average farm size of 0.97 ± 0.04 ha comprises 12.31 % of the surveyed HHs. This farm type exhibits the largest number in regard to work on-farm (2.93 ± 0.21) and has the lowest percentage of their acreages under paddy (8.14 ± 1.87 %). These are primarily cereals and cash crop producers with 31.80 ± 3.68 % and 58.58 ± 6.50 % of their arable land under these classes, respectively. Their average livestock size is 2.70 ± 0.16 TLU, which chiefly comprises milch cattle (cow), goatery, and poultry. In regard to overall income from farms, crop contributes to 66.55 ± 2.41 %, while livestock and off-farm work dispenses 31.42 ± 2.29 % and 2.39 ± 1.17 %, respectively.
6. FT6 (Marginal farmer paddy-wheat and poultry-dairy livestock) has the lowest proportion in sampled HHs (0.44 %) and the smallest landholding (0.60 ± 0.12 ha). This farm type leads in the sale of cereal and fodder produce, with 62.50 ± 23.94 % and 50.00 ± 28.87 % of the total being sold to the market, respectively. The average livestock size is 127.00 ± 25.27 TLU, which is the largest among the developed farm types and is chiefly due to the greater scale of poultry keeping among the producer group. Crop and livestock income contribute nearly the same proportion to the overall income, which are 50.23 ± 10.20 % and 49.77 ± 10.20 %, respectively.

Demographically, FT2 is distributed most evenly and is present in 25 districts, while FT6 has the most asymmetric distribution and is present in only 02 districts, namely, Purnea (Bihar) and Samba (J&K). In regard to farm type composition, Chhetinad (Tamil Nadu) and Pakur (Jharkhand) have only a single farm type (FT2), followed by Angul & Kendrapara of Odisha, having only 2 farm types (FT2 & FT4). Further, 03 and 04 farm types were exhibited by 34.62 % of districts each, while only 15.38 % have 05 farm types. None of the surveyed districts has all six farm types. District and state-wise distribution of the developed farm types and composition of farm types in the surveyed district is depicted in Fig. 6. Concerning the composition of ACZ in terms of developed farm types, it was observed that the Central Plateau & Hills and Eastern Himalayan Region have a composition of 03 farm types, namely, FT1, FT2, and FT3, respectively. Six ACZs, viz., East Coast plains & hills region, Eastern plateau & hills region, Middle Gangetic plains region, Trans

Fig. 3. Biplots for the input variables.

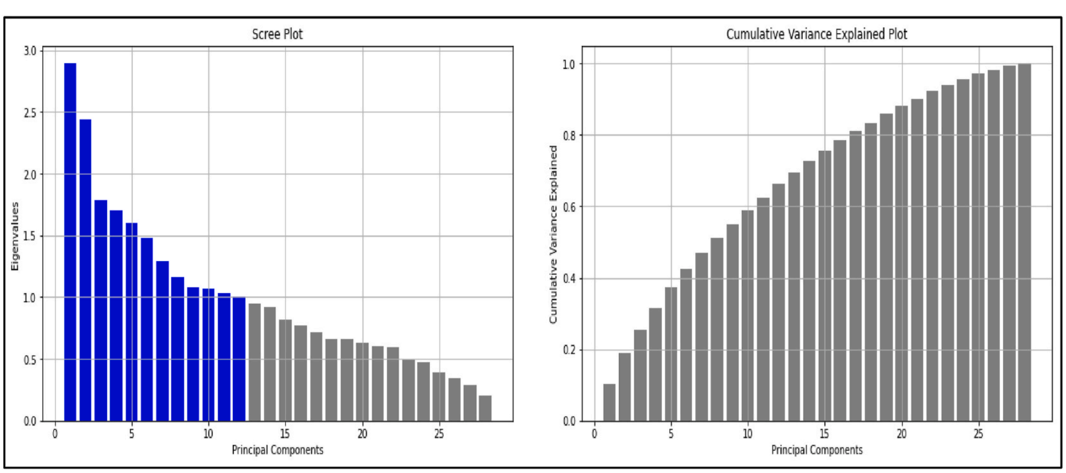

Fig. 4. Scree plot (with legitimate PCs in blue) and cumulative variance explained by the PCs.

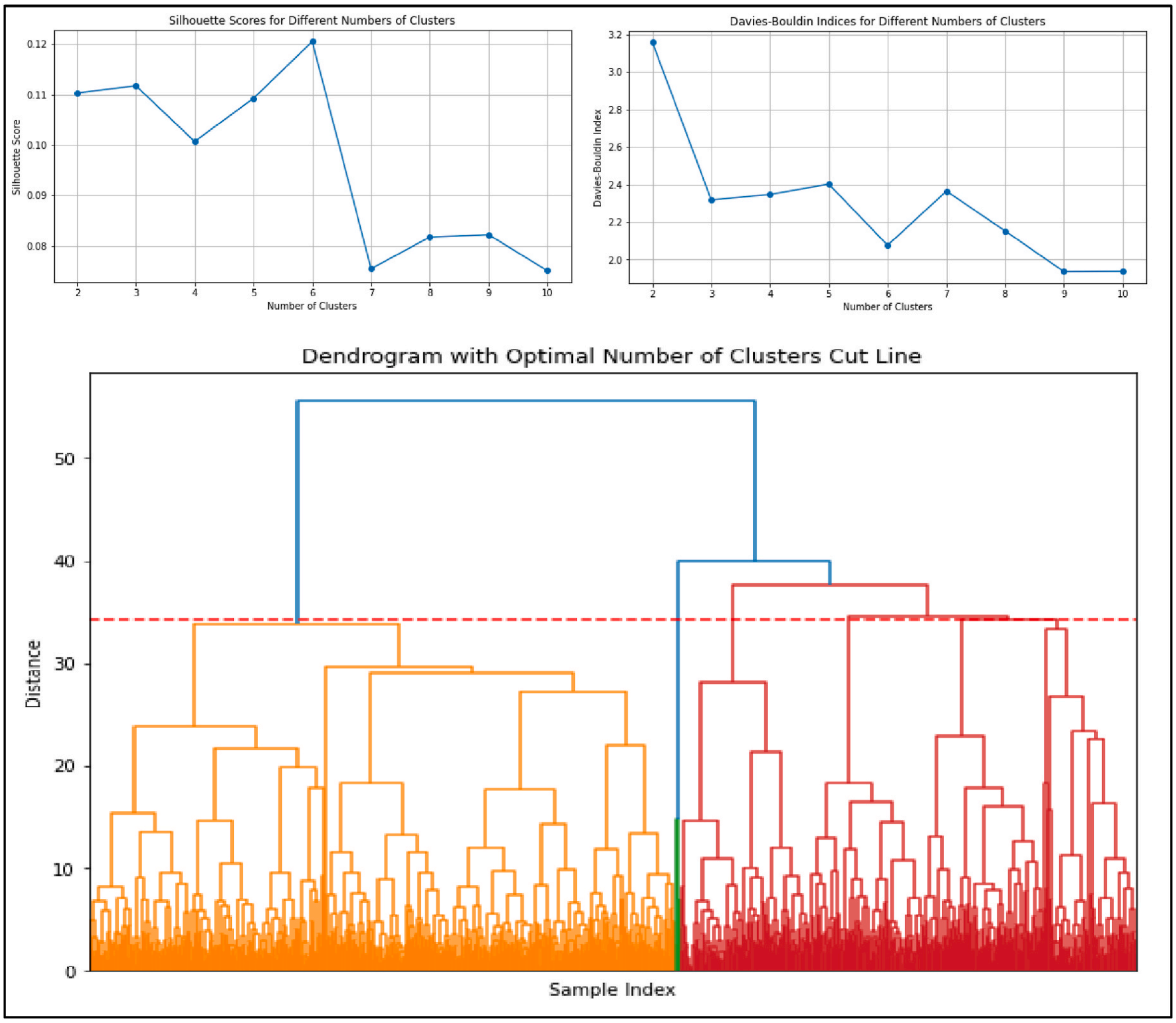

Fig. 5. Silhouette score, DB index, and Dendrogram for the optimal number of clusters.

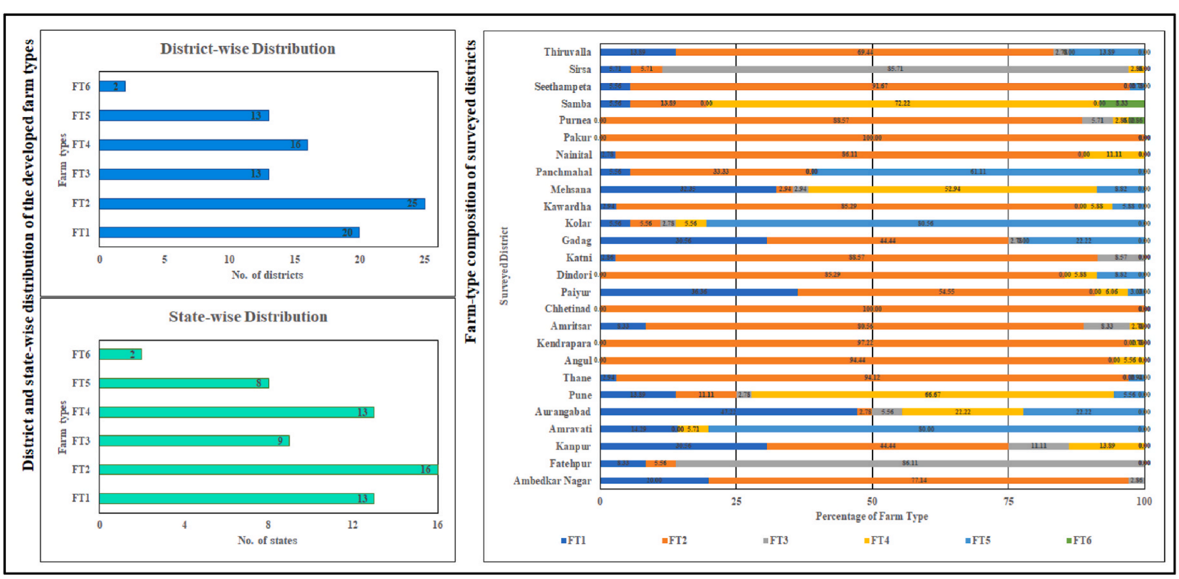

Fig. 6. District and state-wise distribution of farm types and farm composition of surveyed districts.

Gangetic plains region, Upper Gangetic plains region, and Western Himalayan region, have 04 categories of the developed farm types. The remaining 04 ACZs, namely, Gujarat plains & hills region, Southern Plateau & hill region, West coast plains & Ghat region, and Western Plateau & hills region, consist of 05 different farm types.

4. Discussion

4.1. Scoping for diversification in developed farm types

The contemplated study highlights the distinguishing characteristics of farming systems via multiple factors such as household assets, climatic & soil conditions, crop production, livestock, income, and market attributes. These factors influence the strategies and decision-making of the considered farms under any hostile condition due to climatic vagaries such as crop failure, droughts, etc., unexpected expenditures, declining soil fertility, land fragmentation, etc., and reflect the inherent diversity in farm management strategies (Kuivanen et al., 2016). The relationship of these factors with the clustered farm types, along with suggested interventions, is discussed in the successive sub-sections. The KW test, due to the non-normal distribution of the input variables, was executed to identify a significant difference in the developed farm types among the considered parameters. Table 2 provides a comprehensive overview of different farm types, highlighting significant differences in various agricultural and economic domains.

4.1.1. HH demographics

The surveyed HHs predominantly consist of small and marginal farms, with average land holding sizes ranging from 0.60 ha to 1.11 ha. There is no significant difference in holding size across different farm types. Similarly, the average age of farmers and no. of children across the different farm types showed no significant difference, indicating a uniform distribution in age (47.2–50.0) as well as in no. of children. Dietary Preferences concerning the number of vegetarians and non-vegetarians show significant differences, with FT3 having the highest number of vegetarians (4.48) and the lowest number of non-vegetarians (0.36) in the family.

4.1.2. Labor

Typically, family labor is based on kinship ties and traditionally is considered the backbone of the rural workforce. It often reduces the cost of production, leading to improved economic viability, fosters a sense of collective identity & responsibility, facilitates the transfer of traditional knowledge and skills, and allows for greater adaptability & resilience (Gupta, 1998; Singh and Sidhu, 2004; Swaminathan, 2006). The availability of labor has a significant impact on the choice of farming system, particularly in smallholder settings. There are significant differences in the number of on-farm workers across the developed farm types, with FT5 having the highest number (2.93) and FT3 the lowest (1.09). On the other hand, there is no significant difference in the number of off-farm workers (hired labor) across the clustered farm types, suggesting the limited fiscal capacity of small/marginal farmholders and aligning with the typical observation of rural labor constraints. This is consistent with the earlier typology studies from India and Sub-Saharan Africa, where household labor is a key driver in shaping the structural orientation and intensification level of farms (Carelsen et al., 2021; Kaur et al., 2021; Eshetae et al., 2024) Typically, more labor is required in the cultivation of fruits and vegetables; therefore, induction of horticulture-based diversification is relatively challenging in farm types having significantly less no. of agricultural labor (Kaur et al., 2021). Similarly, labor constraints often restrict the adoption of diversified nutritional farming models (Timler et al., 2017). For such farm types, crop diversification with less labor-intensive crops such asoil seeds and cereals appears to be a more competent strategy.

4.1.3. Crops

Different farming systems focus on growing specific types of crops. Some farming HHs prioritize staple food crops like rice, wheat, maize,

Table 2
Characteristics of developed farm types.

Farm Type	S	A	WonF	WoffF	Ch	NV	V	Pint	Wint	CEint	fodint	Cashint	othercropint
FT1	0.84^{a}	47.22^{a}	1.38^{c}	2.53^{a}	2.49^{a}	2.20^{a}	2.71^{b}	24.37^{b}	23.15$^{b c}$	17.30$^{a b c}$	22.36^{a}	36.19$^{b c}$	9.76^{b}
FT2	0.87^{a}	45.86^{a}	1.53^{c}	2.38^{a}	2.49^{a}	3.30^{a}	1.53^{c}	66.04^{a}	27.69^{b}	18.29^{c}	1.81^{b}	33.55^{c}	5.70^{b}
FT3	1.11^{a}	45.33^{a}	1.09^{d}	2.36^{a}	2.70^{a}	0.36^{b}	4.48^{a}	10.68^{b}	69.72^{a}	53.71$^{a b}$	13.99^{a}	58.37^{a}	37.75^{a}
FT4	0.83^{a}	47.46^{a}	1.76^{b}	2.32^{a}	2.49^{a}	1.98^{a}	2.99^{b}	14.18^{b}	19.86^{b}	15.03$^{b c}$	28.89^{a}	34.23^{c}	9.90^{b}
FT5	0.97^{a}	48.45^{a}	2.93^{a}	2.02^{a}	2.79^{a}	1.97^{a}	3.41^{b}	8.14^{b}	1.56^{c}	31.80^{a}	4.66^{b}	58.58$^{a b}$	14.36^{b}
FT6	0.60^{a}	50.00^{a}	1.25$^{c d}$	1.75^{a}	3.25^{a}	5.25^{a}	0.00^{c}	23.94$^{a b}$	0.53$^{b c}$	15.63^{c}	21.88^{a}	0.00^{c}	8.13^{b}

Farm Type	Pyield	Wyield	Rhome	Rsold	Whome	Wsold	CEhome	CEsold	fodHH	fodsold	CChome	CCsold	Othercropshome
FT1	2579.71^{b}	2324.09$^{b c}$	10.69^{b}	34.50^{c}	21.19^{b}	24.96^{b}	72.08^{a}	19.17^{b}	30.09^{a}	18.91^{a}	48.39^{a}	10.23$^{a b}$	3.25^{b}
FT2	3892.48^{a}	1883.99^{c}	53.00^{a}	45.45^{b}	29.29^{b}	35.17^{b}	3.89^{c}	3.29^{d}	22.88^{a}	18.26^{a}	33.53^{b}	16.34^{a}	11.63^{a}
FT3	1153.49^{c}	4468.30^{a}	17.67^{b}	69.99^{a}	34.64^{a}	55.49^{a}	2.72^{c}	14.57^{c}	18.72$^{a b}$	2.27$^{a c}$	27.42^{b}	3.44^{c}	1.57^{b}
FT4	2953.58^{b}	2514.89^{b}	30.21^{b}	24.79$^{c d}$	37.59$^{a b}$	36.61^{b}	3.30^{c}	92.70^{a}	18.38$^{a b}$	20.60$^{a b}$	36.99$^{a b}$	7.96$^{b c}$	2.13$^{a b}$
FT5	412.54^{c}	568.61^{d}	8.03^{b}	7.90^{d}	10.42^{b}	23.21^{b}	2.30^{c}	2.12^{d}	11.36^{b}	11.64$^{a b c}$	36.99$^{a b}$	6.36$^{b c}$	1.61^{b}
FT6	2441.67$^{b c}$	1642.86$^{c d}$	47.03$^{a b}$	27.97$^{c d}$	40.31$^{a b}$	34.69^{b}	31.25^{b}	62.50$^{a b}$	0.00^{b}	50.00^{a}	17.86^{b}	7.14$^{b c}$	2.19$^{a b}$

Farm Type	OCsold	Cow	Buffalo	Calf	Sheep	Goat	Pig	Chicken	TLU	Cincome	Lincome	FISHincome	OFFincome
FT1	21.74^{b}	0.98^{a}	0.73$^{b c}$	1.22$^{a b}$	0.01^{b}	0.51$^{a b}$	0.00^{b}	1.03$^{c d}$	2.21^{b}	65.05$^{b c}$	33.69^{a}	0.00^{a}	1.28^{a}
FT2	19.05^{b}	0.95^{a}	0.51^{c}	1.52^{a}	0.01^{b}	0.90$^{a b}$	0.09^{a}	3.15^{b}	2.51^{b}	77.70^{a}	17.28^{b}	0.47^{a}	5.88^{a}
FT3	51.52^{a}	0.59^{a}	1.22^{a}	1.54^{a}	0.05^{b}	1.41^{a}	0.00^{b}	0.04^{d}	2.50^{b}	58.12$^{b c}$	41.61^{a}	0.00^{a}	0.26^{a}
FT4	23.87^{b}	0.89^{a}	1.06$^{a b}$	0.97^{b}	0.00^{b}	0.43$^{a b}$	0.00^{b}	0.66^{d}	2.15^{b}	56.49^{c}	42.14^{a}	0.05^{a}	1.32^{a}
FT5	41.75^{a}	1.12^{a}	0.65$^{b c}$	1.69^{a}	0.26^{a}	1.23$^{a b}$	0.04$^{a b}$	1.19$^{b c}$	2.70^{b}	66.55^{b}	31.42^{a}	0.01^{a}	2.39^{a}
FT6	22.81^{b}	1.25^{a}	0.75$^{a b c}$	0.75^{b}	0.00^{c}	0.75^{a}	0.00^{b}	1250.00^{a}	127.00^{a}	50.23^{c}	49.77^{a}	0.00^{a}	0.00^{a}

[a] value is significantly higher with respect to 'b'.
[b] value significantly lower than 'a' but higher than 'c'.
[c] value lower than 'b', but higher than 'd'.
[d] significantly lowest among all value.

etc., while others opt for specializing in cash crops like coffee, tobacco, sugarcane, etc. The developed farm types have displayed a considerable variation choice/selection of crops as depicted by the contrasting cropping intensities. Significant differences are noted in paddy intensity across developed farm types, with FT2 and FT5 having the highest and lowest percentages, which are 66.04 % and 8.14 %, respectively. Further, there is a significant difference in paddy yields, with FT2 demonstrating the highest paddy yield of 3892.48 kg/ha, making it the most rice-intensive system. Similarly, in the context of wheat yield, farm type FT3 displayed the highest (4468.30 kg/ha), reflecting a mono-cropping pattern. FT3 shows a significantly higher wheat intensity (69.72 %), followed by FT2 (27.69 %). Further, higher cash crops (58.37 %) and other crops (37.75 %) intensities were observed for FT3. It is to be noted that the FT1, which represents diversified farmers, has paddy intensity at par with FT2, and has adopted a balanced approach towards crop cultivation and subsequent diversification. The FT1 endorses paddy and wheat as primary crops while following relatively balanced intensities for other cereal crops (17.3 %), cash crops (36.19 %), and horticulture crops (9.76 %). The farm type FT4 integrates crop cultivation (rice and wheat) and livestock rearing on the same farm, with significantly higher fodder intensity (28.89 %), and balanced livestock units (average of 02 milch animals), allowing farmers to diversify their agricultural activities and make more efficient use of available resources. The farm type FT5 showed a strong commercial orientation with significantly higher cash crop intensity (58.58 %), cereal intensity (31.80 %), and off-farm income (2.93 %). The amount of produce retained for household consumption versus that marketed varies notably among the identified farm types, indicating differing production goals, levels of subsistence, and market integration. Such variation reflects both economic capacity and resource endowment — with market-oriented clusters typically linked to higher productivity and better access to infrastructure (Carelsen et al., 2021). Subsistence-dominant types, in contrast, tend to prioritize food security over surplus generation, a pattern also observed in typology studies across sub-Saharan Africa and South Asia (Table 2). Induction of alternative crops in paddy-wheat and wheat-dominated systems for all farm types (excluding FT1), such as maize, pulses, lentils, oilseeds, and horticulture crops such as vegetable crops and fruits, can provide an additional income stream as well as nutrition diversity (FAO, 2002). This type of crop diversification intervention shall also assist in breaking pest cycles and improve soil fertility & health (Khalsa et al., 2019; Kumar et al., 2020). These results suggest that traditional paddy-wheat rotations remain dominant with low crop diversification across most farm types, except for FT1 (which balances staple grains with cash crops and horticulture). The significantly higher proportion of produce sold in FT5 and FT2 indicates that these farm types are better integrated into market networks, whereas FT3 and FT4 still retain substantial portions for home consumption. This suggests the need for enhanced market linkages, storage, and value chain integration for wheat-dominated and mixed-farming systems.

4.1.4. Livestock

There is a significant variation in the number and types of livestock, with some farm types focusing more on livestock farming. FT6 has the highest number of TLU (127.0) primarily due to large-scale poultry rearing, which has been widely recognized as a low-input, high-output enterprise in marginal farming communities. Also, significant differences exist among specific livestock such as cows, buffaloes, calves, sheep, goats, pigs, and chickens across the developed farm types, with TLU ranging from 2.15 to 2.70, respectively. FT6 has the highest number of cows (1.25), while FT3 has the highest number of buffaloes (1.22), suggesting a focus on dairy-based production systems. The farm types FT3 and FT4 maintain a greater livestock diversity following the presence of chickens, goats, and sheep, with the TLU of 2.50 and 2.15, implying integration of milch buffalo and cattle as a complementary income source to wheat and paddy cultivation. Additionally, the cultivation of fodder crops suggests a well-rounded approach towards livestock management, thus contributing to the overall agricultural dynamics. These farm types have a significant portion of total income coming from livestock, which is 41.61 % and 42.14 %, respectively. Thus, the major area of targeted interventions for these farm types lies in enhancing fodder cultivation, which directly supports livestock productivity and income generation. Studies have shown that insufficient on-farm fodder is a key constraint to realizing the full potential of livestock-based income, especially in mixed and marginal systems (Balehegn et al., 2020). Promoting dual-purpose crops, improved pasture species, and seasonal fodder planning can significantly strengthen the livestock component of integrated farming systems. This shall also assist in augmenting the household's nutritional security. The farm types FT2 and FT5 have comparable TLU and livestock income, but still, the contribution of livestock sources is relatively less than that of crops. For FT1 to FT5, further intensification of livestock, along with strengthening of fodder crops and other cereal crops, is suggested as they exhibit intermediate livestock ownership, reflecting their engagement in a combination of milch animals, goatery, and poultry for household needs and market sales. This can be realized through the induction of milch breeds suited to local conditions, leading to better productivity in dairy and the introduction of indigenous and dual-purpose birds to support poultry (Kumawat et al., 2021). Similarly, for HHs in harsh environments having marginal lands, goatery is a viable option as goats provide milk, meat, and fibre, making them a versatile livestock option (Gupta et al., 2020). In HHs having easy access to water bodies, sustainable aquaculture practices such as integrated fishing farming and polyculture are suggested. Further, for all the farm types, induction of apiculture is also recommended. This shall enhance crop productivity via pollination management, especially in horticulture, and would provide products such as honey, bee wax, pollens, propolis, etc., for additional income. Further, induction of small ruminants (goats, sheep) to mitigate climate risks in FT2 and FT3, development of cooperative-based dairy market linkages to improve fair price realization for milk products in FT4 and FT5, strengthening of backyard poultry systems by expanding vaccination programs and feed subsidies in FT6, promoting agroforestry-fodder models in FT3 and FT4 to ensure sustainable livestock feed availability & reducing reliance on external feed inputs, and augmenting livestock insurance programs to protect against disease outbreaks and climate shocks in farm types where livestock income is substantial is recommended.

4.1.5. Farm income

Income distribution in farming systems can vary among different types of farms, depending on various factors such as farm size, type of crops produced, livestock goods, location, market conditions, and access. Typically, small-scale and subsistence farming systems usually exhibit a more equitable distribution of income, as it is primarily derived from the labor and resources available on the farm (Smith, 2020). While this income can often cover the primary necessities of the family, it is typically insufficient for generating substantial profits or fostering growth. For the developed farm types, the results showed marked differences in the amount and sources of income, with certain farm types excelling in specific areas. In the context of income from crops, FT2 had the highest reliance on crop-based sources, where a substantial portion of the total income (77.70 %) is derived from crop-related activities, indicating a strong dependence on agricultural output and market price fluctuations. This was followed by FT5 (66.55 %) and FT1 (65.01 %), with both of these farms exhibiting the highest income diversification, with substantial earnings from both livestock and off-farm employment, reducing their financial vulnerability. The farm type FT6 has the lowest contribution from crop income, which is 50.23 %. Concerning the income from livestock, FT6 has a strong reliance as a substantial portion of its total income (49.77 %) is from livestock goods. This was followed by FT4 and FT3 with livestock income percentages of 42.14 % and 41.61 %, respectively. In contrast, FT2 has the lowest percentage (17.28 %), suggesting a relatively lower contribution from livestock avenues. Further, it was noted that some HHs have fishery also as a contributing income source. For the farm type FT2, 0.47 % of the total income is from fish cultivation, while the rest have negligible or zero income from this particular source. However, income from the fishery displayed no significant difference across the developed farm types. Additionally, off-farm income is also an income diversification sect among the developed farm types, though it exhibits no significant variation among the clustered farming systems. The farm type FT2 has the highest contribution from off-farm income sources, which is 5.88 %. In the case of farm types with more dependency on income from staple grains (FT2), strengthening of the crop insurance mechanism, expansion of procurement systems for cereals, and stabilization of Minimum Support Price (MSP) for cereals/grains are suggested for income resilience and guard against production shocks. For farm-type FT3 and FT4, it is recommended to improve the livestock contribution to overall income for enhancing farm resilience and income diversification. Cross-breeding programs, establishment of village-level self-reliant cooperatives, and de-centralized fodder banks can assist in this regard. This would aid in providing a regular income source, leading to stabilized HH finances, utilization of non-arable lands, and a buffer for managing risks in case of crop failures. For FT5 and FT6, where cash crops contribute significantly to farm income, price volatility and export restrictions pose additional risks. Strengthening value chain integration, improving direct market access, and adopting inclusive contract farming models are key to enhancing the financial resilience of smallholders. Contract farming, when equitably structured, can improve access to quality inputs, credit, and assured markets, though its effectiveness depends on transparent arrangements and regulatory oversight (Narayanan, 2014). Despite such opportunities, off-farm income remains relatively low across all identified farm types, highlighting the seasonal and fragmented nature of non-agricultural employment in rural India. Engagement in off-farm activities such as wage labor, agro-processing, micro-enterprises, and rural services can act as a stabilizing income source, particularly in the face of agrarian risks. This observation aligns with broader rural transformation literature, which emphasizes the role of diversified income portfolios in improving rural livelihoods (Barrett et al., 2015). To strengthen off-farm income opportunities, rural development efforts must prioritize skill-building programs in agri-business, promotion of Self-Help Groups (SHGs)—especially women-led collectives—and the integration of non-farm enterprises like farm-based tourism and value-added production. SHGs in particular have shown promise in mobilizing social capital, enhancing financial inclusion, and creating localized microenterprises (Nayak et al., 2020; Ghosh and Ghosh, 2024). Fig. 7 illustrates the spatial distribution of the farm types in various ACZs across the country.

4.2. *Alternative farming system models*

Typically, an innovative approach to agricultural practices suggests that agro-climatic region-based models are generally more appropriate than strictly adhering to traditional, area-specific farming systems. This approach is based on the hypothesis that a farming system successful in one region with certain agro-climatic conditions is usually effective in another region with similar agro-climatic attributes. Hence, for the developed 06 farm types, suitable farming systems were recommended based on the on-station IFS models developed and evaluated for their performance in the respective ACZs. The recommended models typically integrate various agricultural components, leading to a shift towards more diversified income sources and sustainable agricultural practices, and emphasize the potential benefits of adopting the same. Fig. 8 illustrates the recommendations for alternate farming systems for FT1 to FT6 in different ACZs.

For the FT2 farm type, which is observed in all the 12 ACZs and has the maximum no. of sample HHs (56.10 %), several alternative farming models were suggested for 86.02 % of the cluster population. 08 alternative farming models were recommended for FT2 for 08 ACZs. In the Central plateau & hills and East coast plains & hills (crop + dairy + horticulture + fishery + poultry) model is suggested, while for the Eastern plateau & hills, 'duckery' is also added in the proposed model. Likewise, for the Eastern Himalayan region, 'dairy' and 'poultry' are replaced with apt livestock depending upon the geographic location and altitude of the farm type within the ACZ. For the Middle Gangetic plains and Western Himalayan region (crops + dairy + horticulture + mushroom + vermicompost + NADEP + boundary plantation + poultry) is suggested, while for the Trans-Gangetic plains, the same model is revised following the exclusion of 'NADEP' and 'poultry' and inclusion of 'biogas' generation units. Correspondingly, in the West Coast plains & ghats, it is updated with 'fishery', while 'poultry' and 'mushroom' cultivation were excluded. Similarly, for farm type FT5, which covers 12.31 % of the samples HHs, four alternative farming systems recommendations were made in 04 ACZ covering 76.32 % of the cluster. These are (i) (crops + dairy + duckery + poultry + vermicompost + boundary plantation) for Eastern plateau & hills, (ii) (crops + dairy + horticulture + goatery + vermicompost + boundary plantation + kitchen gardening) for Southern plateau & hills, (iii) (crops + + horticulture (fruit crops + nursery) + dairy + goatery + vermicompost + boundary plantation + kitchen gardening + poultry) in West coast plains & hills, and (iv) (crops + dairy + horticulture + goatery + poultry + vermicompost) in Western Plateau & hills, respectively. For farm type FT1 (covering 11.33 % of surveyed HHs) 08 alternative models were proposed at 08 ACZs, namely, (crops + agri. horticulture + dairy + vermicompost + boundary plantation) in Central Plateau and hills, (crops + livestock + horticulture + fishery) in Eastern Himalayan region, (crops + dairy + vermicompost + mushroom + apiary + fishery) in Eastern Plateau & hills, (crops + dairy + season vegetables + vermicompost + Azolla + nursery + boundary plantation + water harvesting) in Gujarat plains & hills, (crops + dairy + sheep + poultry + horticulture + compost) in Southern Plateau & hills, (plantation crops + goatery + duckery + fishery) in West Coast plains & ghats, (crops + dairy + horticulture + fodder + vermicompost + boundary plantation + kitchen gardening) in Western Himalayan region, and (crops + dairy + horticulture + vermicompost + boundary plantation) for Western Plateau & hills, respectively. These proposed models account for potential interventions for 79.81 % of the FT1 population. In the same way, alternative models are proposed for 02 ACZs of FT3 covering 6.17 % of the cluster populace, 10 ACZs of FT4 concealing 100 % of the cluster, and 1 ACZ of FT6 enveloping 25 % of the cluster population. These can be apprehended from Fig. 8.

A cluster-wise comparison of annual income for the current and the proposed alternative farming system model is also consummated in the study. For FT1, following the recommended alternative farming models, an increase of 11.50 % in the annual income is observed for the Central Plateau & hills, while an increment of 1235 % in the annual revenue is perceived for the Eastern Himalayan region. Likewise, following the proposed models for FT2 in the West Coast plains & ghats can yield growth of 1110.77 %, while in the Trans-Gangetic plains, a rise of 107.98 % in the yearly earnings can be witnessed. Similarly, an intensification of 862.44 % and 202.64 % in the yearly income can be noticed for the Central Plateau & hills and Middle Gangetic plains, following the proposed models for FT3, respectively. For FT4 proposed farming recommendations increase the annual earnings by 2684.91 % and 65.65 % for East Coast plains & hills and Eastern Plateau, while for the FT5 farm type, an increment of 853.94 % and 226.48 % can be apprehended for Western Plateau & hills and Southern Plateau & hills, respectively. In the case of FT6, for which a single proposed model is presented for the Middle Gangetic plains, an increase of 296.86 % can be witnessed. Increment in annual income for other proposed models under various farm types in the considered ACZs can be visualized in Fig. 9.

This comprehensive analysis reveals compelling opportunities to significantly augment annual incomes across diverse agro-climatic zones in India through the adoption of proposed alternative farming models. These models showcase remarkable increases in annual income,

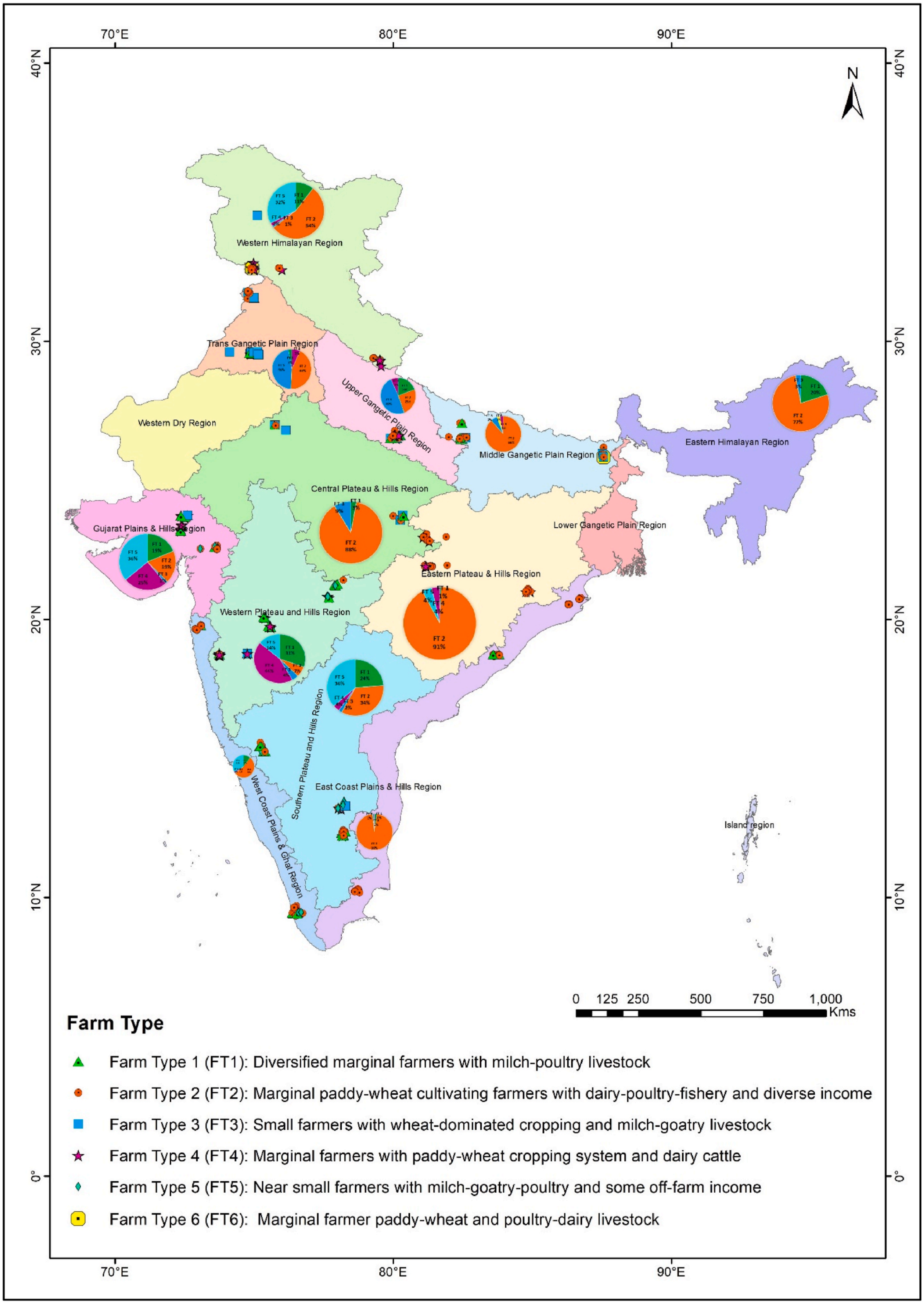

Fig. 7. Distribution of developed farm types across ACZs in India.

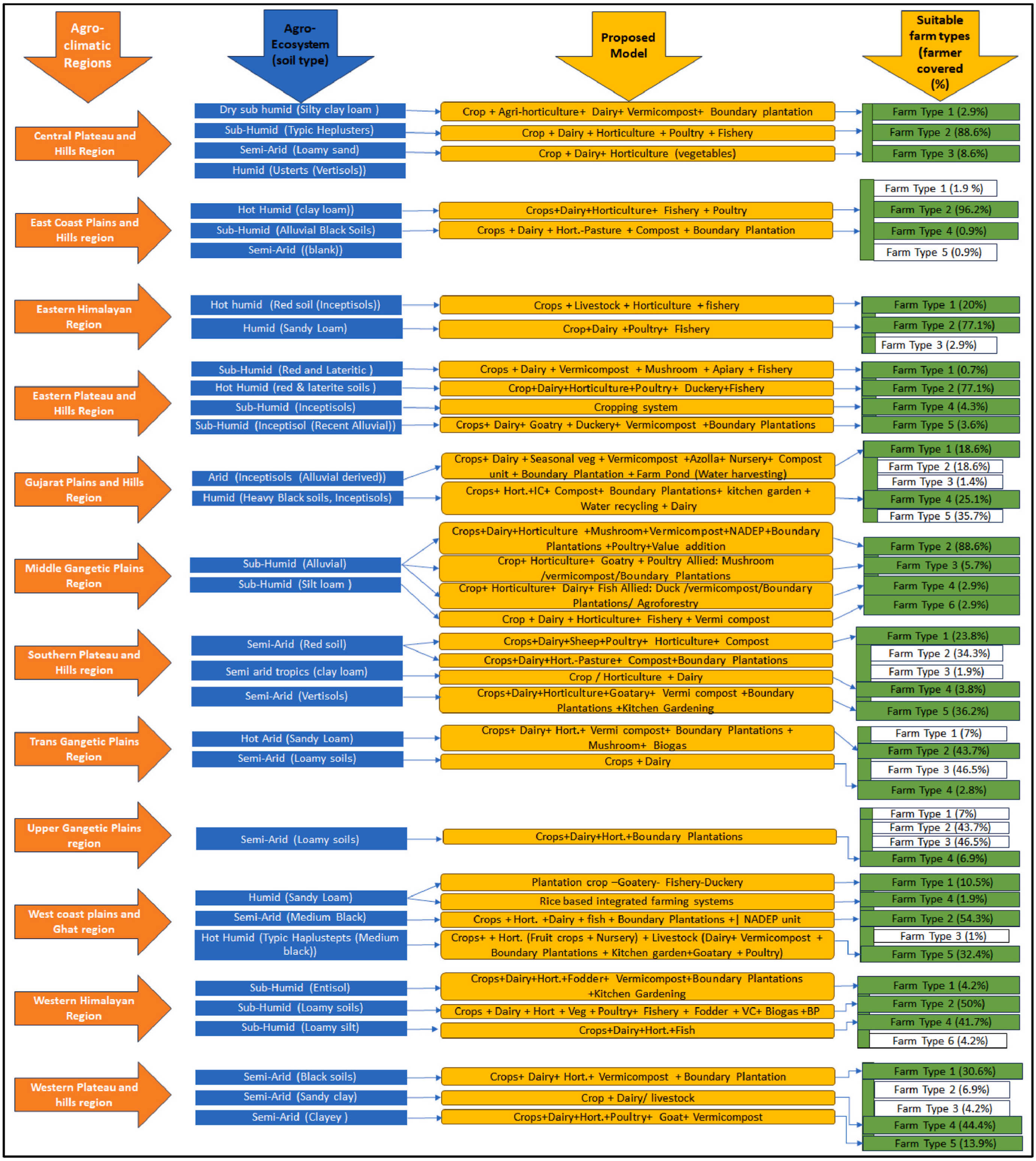

Fig. 8. Alternate farming recommendations for developed farm types in various ACZs.

underscoring their potential impact on farmers' livelihoods. It is particularly important and aligns closely with the doubling farmer's income (DFI) initiative, which aims to enhance farmers' earnings through strategic interventions in agriculture. The observed income increments not only validate the efficacy of these proposed models but also align closely with the DFI's overarching goal. Furthermore, the potential income growths underscore the transformative impact of tailored agricultural strategies suited to specific agro-climatic conditions. By facilitating such advancements, policymakers can effectively support farmers in achieving higher profitability, reducing dependency on conventional practices, and fostering resilience against climate variability. Leveraging these findings to scale up the implementation of the recommended farming models holds promise for realizing the broader socio-economic objectives of the DFI across India's diverse

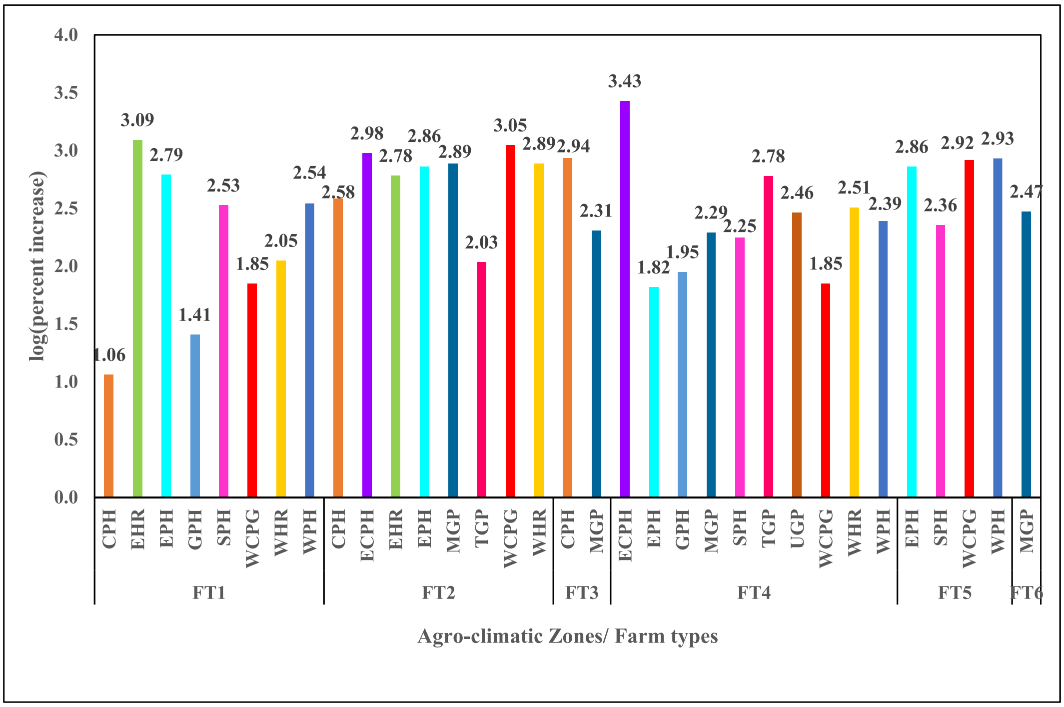

Fig. 9. Increment in annual income following the proposed model for the developed farm types
CPH: Central plateau & hills, HER: Eastern Himalayan Region, EPH: Eastern plateau & hills, GPH: Gujarat plains & hills, SPH: Southern plateau & hills, WCPG: West coast plains & ghats, WHR: Western Himalayan Region, WPH: Western plateau & hills, ECPH: West coast plains & hills, MGP: Mid-Gangetic plains, TGP: Trans-Gangetic plains, UGP: Upper Gangetic plains.

agricultural landscape.

While the proposed models of sustainable intensification—tailored to farm typologies across diverse agro-climatic regions—hold strong promise for enhancing farm income and resilience, their practical implementation faces several challenges. First is the financial and institutional vulnerability of small and marginal farmers, who often lack access to timely credit, quality inputs, and risk mitigation mechanisms. Many of the interventions—such as boundary plantations, fishery units, vermicomposting, horticulture integration, and allied enterprises like poultry, goatery, or mushroom units—require initial capital, technical knowledge, and ongoing support systems, which are often inaccessible to resource-constrained households. Implementation also hinges on the availability of labour, water, and land, all of which are limited in marginal farm settings. For instance, labor-intensive interventions such as horticulture, etc., are less feasible in labor-deficient clusters (e.g., FT3), while dairy or composting units may face constraints in water-scarce or fragmented landscapes. Moreover, fragmentation of holdings, poor rural infrastructure, and low market connectivity hinder the scalability of high-value interventions. Institutional support systems—such as extension services, input delivery, marketing linkages, and price realization mechanisms—are crucial yet often realtively underdeveloped in target geographies. Therefore, implementing the proposed models requires multi-pronged policy and programmatic convergence. Schemes such as PM-KUSUM, RKVY, NABARD refinancing, and Agri-Infrastructure Fund can be leveraged to provide fiscal support through institutional credit, while also facilitating handholding in marketing, input supply chains, and capacity-building programs. Furthermore, for wider and sustained adoption, targeted community outreach mechanisms must be embedded into the model delivery. These include awareness campaigns, social and behavioral change communication (SBCC), demonstration farms, and collaborative participatory research that ensures contextual adaptability. The findings of this study have significant international relevance, particularly for smallholder farming systems in regions such as South Asia, Sub-Saharan Africa, and Latin America, where fragmented landholding, climate risks, and market access challenges persist. The farm typology framework provides a scalable approach for classifying small and marginal farmers based on their production strategies, resource availability, and market engagement. By adopting this classification method, policymakers in different agro-climatic zones can develop targeted interventions that promote diversified and integrated farming systems. Countries with a high dependency on small-scale agriculture, such as Vietnam, Kenya, and Peru, can leverage this approach to enhance farm resilience, improve income diversification, and optimize land use. Furthermore, the alternative farming system models proposed in this study align with international strategies for climate-smart agriculture and sustainable intensification. The integration of livestock, horticulture, and agroforestry into smallholder farms has been successfully implemented in regions like the Sahel in Africa and the Mekong Delta in Southeast Asia, demonstrating the potential for cross-regional adaptation of these models to improve food & nutrition security and rural livelihoods.

Despite its strengths, the study has certain limitations. The farm typology framework is region-specific, and while the methodology is adaptable, the direct applicability of the selected indicators may vary across different agricultural contexts. Socio-economic constraints such as limited access to credit, high initial investment costs, and weak market infrastructure may hinder the adoption of integrated farming systems, particularly for marginal farmers with minimal fiscal capacity. Additionally, while the study focuses on technical feasibility, socio-cultural factors, including traditional land-use preferences and gender roles in agriculture, may influence the willingness of farmers to transition to diversified systems. There may also be short-term yield trade-offs when shifting from monocropping to diversified farming models, necessitating transitional support mechanisms. Future research should explore financial models, participatory approaches, and policy-driven incentives to enhance the scalability and adoption of alternative farming systems across diverse agro-ecological regions.

5. Conclusion

The presented study is an attempt towards the development of a pan-India level typology for farming systems by encompassing 918 HHs from 26 districts across 16 states of India. 39 input variables were determined for the sampled small and marginal farms over which multivariate analysis (PCA + HCA) was applied, leading to the development of 06 farm types. Alternative farming system recommendations were made for the identified 06 clusters based on the on-station IFS models of AICRP. The developed typology is a key towards understanding the patterns and processes involved in small and marginal farming systems. This can be an instrument in tailoring targeted sectoral development policies and legislative agendas for a wider uptake and upscale of sustainable agriculture initiatives. The study can be expanded following the inclusion of additional data types, such as behavioral indicators like compliance rates, sentiment analysis data, behavioral trends, etc., which directly affect policy acceptance, along with expert validation for making the overall typology more robust. Further, institutional support data such as the impact of subsidies, access to credits/soft loan services, level of participation in agri-cooperatives, reach of awareness campaigns/behavioral change communication, etc., and cultural angles like community & social influence, gender role, producer attitude towards innovation/risks, etc., can also be employed. Moreover, the induction of artificial intelligence and machine learning methods can assist in data analysis processes and their subsequent visualization. Nevertheless, the presented work is a contribution to the improved understanding of small and marginal farming systems across different agro-climatic zones of India and shall increase the utility of farm typology studies in the landscape of agricultural policies.

CRediT authorship contribution statement

A.K. Prusty: Writing – original draft, Methodology, Investigation, Funding acquisition, Conceptualization. **N. Ravisankar:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Jashanjot Kaur:** Writing – review & editing, Methodology, Formal analysis. **Himanshu Joshi:** Writing – review & editing, Visualization, Formal analysis, Data curation. **Meenu Rani:** Writing – review & editing, Visualization, Data curation. **Santiago Lopez Ridaura:** Writing – review & editing, Project administration, Methodology, Funding acquisition, Conceptualization. **Jeroen C.J. Groot:** Writing – review & editing, Visualization, Software, Resources, Formal analysis, Conceptualization. **M.L. Jat:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Luis Barba-Escoto:** Writing – review & editing, Visualization, Validation, Formal analysis. **M. Shamim:** Writing – review & editing. **M.A. Ansari:** Writing – review & editing, Conceptualization. **V. Paramesha:** Writing – review & editing. **Kadambot H.M. Siddique:** Writing – review & editing, Conceptualization. **Poonam Kashyap:** Writing – review & editing. **Raghuveer Singh:** Writing – review & editing. **K.J. Raghavendra:** Writing – review & editing. **T.P. Swarnam:** Writing – review & editing. **A.S. Panwar:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Sunil Kumar:** Writing – review & editing, Supervision, Project administration.

Funding

This research was funded by the Indian Council of Agricultural Research-Indian Institute of Farming Systems Research (IIFSR), Modipuram, UP, India, under AICRP on IFS.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript titled "Tailored Framework for Sustainable Intensification of Marginal and Small Farms Using Farm Typology to Strengthen Farm Income." All authors have approved the final manuscript and agree with its submission.

All the authors have nothing to declare.

Acknowledgements:

The authors are thankful to the Chief Agronomists/and Agronomists of All India Coordinated Research Project on Integrated Farming Systems (AICRP-IFS) for cooperation in the execution of the on-station and on-farm studies in their respective jurisdiction and for providing the data. Authors also acknowledge the technical collaboration between AICRP-IFS, CIMMYT, and WUR, The Netherlands.

Data availability

Data will be made available on request.

References

Abdi, H., Williams, L.J., 2010. Principal component analysis. Wiley Interdiscip. Rev. Comput. Stat. 2 (4), 433–459. https://doi.org/10.1002/wics.101.

Alvarez, S., Timler, C.J., Michalscheck, M., Paas, W., Descheemaeker, K., Tittonell, P., Andersson, J.A., Groot, J.C.J., 2018. Capturing farm diversity with hypothesis-based typologies: an innovative methodological framework for farming system typology development. PLoS One 13 (5), e0194757. https://doi.org/10.1371/journal.pone.0194757.

Balehegn, M., Duncan, A., Tolera, A., Ayantunde, A.A., Issa, S., Karimou, M., et al., 2020. Improving adoption of technologies and interventions for increasing supply of quality livestock feed in low- and middle-income countries. Global Food Secur. 26, 100372. https://doi.org/10.1016/j.gfs.2020.100372.

Barrett, C., Christiaensen, L., Sheahan, M., Shimeles, A., Reardon, B.M., McCullough, E., Christian, P., 2015. The structural transformation of rural Africa: on the current state of African food systems and rural nonfarm economies. In: Paper Prepared for the African Economic Research Consortium's Biannual Research Workshop. Addis Ababa, Ethiopia.

Carelsen, C.P.R., Ncube, B., Fanadzo, M., 2021. Classification and characterisation of smallholder farmers in South Africa: a brief review. S. Afr. J. Agric. Ext. 49 (2), 97–106.

Cortez-Arriola, J., Groot, J.C.J., Rossing, W.A.H., Scholberg, J.M.S., Massiotti, R.D.A., Tittonell, P., 2016. Alternative options for sustainable intensification of smallholder dairy farms in north-west Michoacán, Mexico. Agric. Syst. 144, 22–32. https://doi.org/10.1016/j.agsy.2016.02.001.

Dev, S.M., 2012. Small Farmers in India: Challenges and Opportunities. Working Papers 2012-014, 8. Indira Gandhi Institute of Development Research, Mumbai.

Eshetae, M.A., Abera, W., Tamene, L., Mulatu, K., Tesfaye, A., 2024. Understanding farm typology for targeting agricultural development in mixed crop-livestock farming systems of Ethiopia. Farming Syst. 2 (3), 100088. https://doi.org/10.1016/j.farsys.2024.100088.

Eshetae, M.A., Balcha, Y., Yeboah, S., Adimassu, Z., Abera, W., 2025. Farm typology-based strategy for targeted climate-smart agriculture interventions: a case study in the Guinea Savannah agro-ecological zone of Ghana. Climate Smart Agriculture 2, 100050. https://doi.org/10.1016/j.csag.2025.100050.

FAO, 2002. Collecting data on livestock. FAO Statistical Development Series 4. Food and Agriculture Organization of the United Nations, Rome (Reprint 2002). https://www.fao.org/fileadmin/user_upload/esa/docs/1_Collection%20data%20on%20livestock.pdf.

FAO, 2014. The State of Food and Agriculture. Food and Agriculture Organization of the United Nations (FAO). ISBN: 978-92-5-108537-0. http://www.fao.org/3/a-i4040e.pdf.

FAO, 2019. The State of Food and Agriculture 2019. Moving forward on food loss and waste reduction. Rome Licence CC BY-NC-SA 3.0 IGO.

Ghosh, A., Ghosh, A., 2024. Empowering rural women in India: self-help groups as catalysts for development. Futurist. Trends Soc. Sci. 3, 1–16.

Groot, J.C.J., Oomen, G.J.M., Rossing, W.A.H., 2012. Multi-objective optimization and design of farming systems. Agric. Syst. 110, 63–77. https://doi.org/10.1016/j.agsy.2012.03.012.

Gupta, A.K., 1998. The role of traditional knowledge in sustainable development. Tech. Dev. 9 (1), 1–17. https://doi.org/10.1016/S1369-8486(97)00024-5.

Gupta, A., Gupta, V., Shukla, S., 2020. Goat farming: a sustainable livelihood option for small and marginal farmers in India. Int. J. Curr. Microbiol. Appl. Sci. 9 (3), 2876–2881. https://doi.org/10.20546/ijcmas.2020.903.335.

Hazell, P., 2005. Is there a future for small farms? Agric. Econ. 32 (s1), 93–101. https://doi.org/10.1111/j.0169-5150.2004.00027.x.

Hill, R.C., Griffiths, W.E., Lim, G.C., 2011. Principles of Econometrics, fourth ed. Wiley.

Huber, R., Bartkowski, B., Brown, C., El Benni, N., Feil, J.-H., Grohmann, P., Joormann, I., Leonhardt, H., Mitter, H., Müller, B., 2024. Farm typologies for understanding farm systems and improving agricultural policy. Agric. Syst. 213, 103800. https://doi.org/10.1016/j.agsy.2023.103800.

ICAR, 2018. Handbook of Agriculture. Indian Council of Agricultural Research.

ICAR, 2023. All India Coordinated Research Project on Integrated Farming Systems (AICRP-IFS): Models and Practices. ICAR, New Delhi. https://iifsr.icar.gov.in/AICRP-IFS.html.
IIFSR, 2015. Vision 2050. ICAR-IIFSR, Meerut, India.
Innazent, A., Jacob, A., Bindhu, J.S., Joseph, B., Anith, K.N., Ravisankar, N., et al., 2022. Farm typology of smallholders integrated farming systems in Southern Coastal Plains of Kerala, India. Sci. Rep. 12, 333. https://doi.org/10.1038/s41598-021-04148-0.
Jackson, J.E., 1991. A User's Guide to Principal Components. Wiley.
Jolliffe, I.T., 2002. Principal Component Analysis. Springer, New York. https://doi.org/10.1007/b98835.
Kaur, J., Prusty, A.K., Ravisankar, N., Panwar, A.K., Shamim, M., Walia, S.S., et al., 2021. Farm typology for planning targeted farming systems interventions for smallholders in Indo-Gangetic Plains of India. Sci. Rep. 11, 20978. https://doi.org/10.1038/s41598-021-00372-w.
Ketchen, D.J., Shook, C.L., 1996. The application of cluster analysis in strategic management research: an analysis and critique. Strateg. Manag. J. 17 (6), 441–458. https://doi.org/10.1002/(SICI)1097-0266(199606)17:6<441::AID-SMJ819>3.0.CO;2-G.
Khalsa, P., Bali, A.S., Kaur, A., Bhat, Z.A., 2019. Effect of maize-wheat-mungbean cropping system on soil organic carbon fractions, aggregate-associated carbon and soil fertility parameters under conservation agriculture. Arch. Agron Soil Sci. 65 (5), 703–719. https://doi.org/10.1080/03650340.2018.1512658.
Khan, M.Z., Ahamad, M., Singh, N., Tewari, V.K., 2023. Integration of multivariate analysis and machine learning techniques for farm typology in south Asia. Comput. Electron. Agric. 201, 106290. https://doi.org/10.1016/j.compag.2022.106290.
Kiptot, E., Franzel, S., Hebinck, P., 2019. Principal component analysis for investigating the variability in agricultural data: a case Study of maize farms in Kenya. Exp. Agric. 55 (6), 863–878. https://doi.org/10.1017/S0014479718000385.
Kostov, P., McErlean, S., 2006. Using a heteroskedastic extended ordered probit model to investigate farm size and land fragmentation. J. Agric. Econ. 57 (3), 527–542. https://doi.org/10.1111/j.1477-9552.2006.00062.x.
Kuivanen, K.S., Alvarez, S., Michalscheck, M., Adjei-Nsiah, S., Descheemaeker, K., Mellon-Bedi, S., Groot, J.C.J., 2016. Characterising the diversity of smallholder farming systems and their constraints and opportunities for innovation: a case study from the Northern Region, Ghana. NJAS - Wageningen J. Life Sci. 78 (1), 153–166. https://doi.org/10.1016/j.njas.2016.04.003.
Kumar, M.D., Singh, O.P., Sharma, S.K., Chauhan, S., 2014. Irrigation efficiency in India: a state-level analysis. Agric. Econ. Res. Rev. 27 (1), 79–89. https://doi.org/10.5958/j.0974-0279.27.1.010.
Kumar, A., Mishra, J.S., Sharma, D., 2020. Growth and yield attributes of maize (*Zea mays L.*) as influenced by varieties, levels of nitrogen and plant density under eastern Uttar Pradesh conditions. J. Pharmacogn. Phytochem. 9 (3), 1550–1554.
Kumawat, P.R., Singh, R., Singh, R., 2021. Indigenous poultry breeds: a sustainable approach for rural poultry farming in India. Indian J. Anim. Res. 55 (1), 106–111. https://doi.org/10.18805/ijar.v55i1.12911.
Milán, M.J., Bartolomé, J., Quintanilla, R., García-Cachán, M.D., Espejo, M., Herráiz, P. L., Caja, G., 2006. Structural characterisation and typology of sheep farms for the cheese production in Spain. Small Rumin. Res. 72 (1), 73–79. https://doi.org/10.1016/j.smallrumres.2006.09.001.
Ministry of Agriculture India, 2014. National Mission on Sustainable Agriculture: Operational Guidelines. http://nmsa.dac.gov.in/pdf/NMSA_Guidelines_English.pdf. (Accessed 7 October 2024).
Montgomery, D.C., Peck, E.A., Vining, G.G., 2012. Introduction to Linear Regression Analysis, fifth ed. Wiley.
Mowo, J.G., et al., 2020. Application of principal component analysis in characterizing the variability of smallholder farming systems in Sub-Saharan Africa: a review. Agronomy 10 (9), 1245. https://doi.org/10.3390/agronomy10091245.
Nagdeve, M.B., 2013. Land fragmentation and consolidation in Indian agriculture: an assessment. Agric. Econ. Res. Rev. 26 (2), 229–240. https://doi.org/10.5958/j.0974-0279.26.2.019.
Nakasujja, N., Mugonola, B., Tenywa, M.M., Woomer, P.L., 2022. Multivariate analysis of smallholder farming systems in East Africa: a case Study of Uganda. Agriculture 12 (1), 76. https://doi.org/10.3390/agriculture12010076.
Narayanan, S., 2014. Profits from participation in high value agriculture: evidence of heterogeneous benefits in contract farming schemes in India. Food Policy 44, 142–157. https://doi.org/10.1016/j.foodpol.2013.10.010.
Nayak, A.K., Panigrahi, P.K., Swain, B., 2020. Self-help groups in India: challenges and a roadmap for sustainability. Soc. Responsib. J. 16 (7), 1013–1033. https://doi.org/10.1108/SRJ-02-2019-0054.
Nguyen, T.L., et al., 2022. Principal component analysis of smallholder farms: a case Study in Northern Vietnam. J. Agri. Sci. 160 (2), 119–132. https://doi.org/10.1017/S0021859622000491.
Niranjan, S., 2014. Fragmentation of agricultural holdings in India: an overview. Indian J. Agric. Econ. 69 (3), 314–323. https://www.researchgate.net/publication/268824539_Fragmentation_of_Agricultural_Holdings_in_India_An_Overview.
NITI Aayog, 2015. Raising Agricultural Productivity and Making Farming Remunerative for Farmers. NITI Aayog, New Delhi, India. https://niti.gov.in/writereaddata/files/document_publication/Raising%20Agricultural%20Productivity%20and%20Making%20Farming%20Remunerative%20for%20Farmers.pdf.
NSSO, 2014. *Key Indicators of Employment and Unemployment in India*, Ministry of Statistics and Programme Implementation. Government of India. http://mospi.nic.in/sites/default/files/publication_reports/nss_report_554_31jan14.pdf.
Pallant, J., 2021. SPSS Survival Manual: a Step by Step Guide to Data Analysis Using IBM SPSS. McGraw-Hill Education.
Paramesh, V., Kumar, P., Shamim, M., Ravisankar, N., Arunachalam, V., Nath, A.J., Mayekar, T., Singh, R., Prusty, A.K., Rajkumar, R.S., et al., 2022. Integrated farming systems as an adaptation strategy to climate change: case studies from diverse agro-climatic zones of India. Sustainability 14, 11629. https://doi.org/10.3390/su141811629.
Pedersen, M.L., et al., 2021. Using principal component analysis to identify spatial patterns in farm-level data: a case Study of organic dairy farms in Denmark. J. Rural Stud. 81, 64–76. https://doi.org/10.1016/j.jrurstud.2021.02.016.
Pew Research Center USA, 2023. Key Facts About India's Growing Population as it Surpasses China's Population. https://www.pewresearch.org/fact-tank/2023/04/21/key-facts-about-indias-growing-population-as-it-surpasses-chinas-population/. (Accessed 7 October 2024).
Pretty, J., 2008. Agricultural sustainability: concepts, principles and evidence. Phil. Trans. Royal Society B: Bio. Sci. 363 (1491), 447–465. https://doi.org/10.1098/rstb.2007.2163.
Prusty, A.K., Ravisankar, N., Panwar, A.S., Jat, M.L., Tetarwal, J.P., López-Ridaura, S., et al., 2022. Redesigning of farming systems using a multi-criterion assessment tool for sustainable intensification and nutritional security in Northwestern India. Sustainability 14 (7), 3892. https://doi.org/10.3390/su14073892.
Rao, N.H., 2017. Big data and climate smart agriculture—Status and implications for agricultural research and innovation in India. Proceedings Indian National Sci. Aca. 83 (3), 621–628. https://doi.org/10.16943/ptinsa/2017/48962.
Rehman, T., Van Ittersum, M.K., Leffelaar, P.A., 2003. Assessing potential impacts of crop management strategies on food self-sufficiency of farm households using system dynamics and sensitivity analysis. Food Policy 28 (6), 523–545. https://doi.org/10.1016/j.foodpol.2003.08.001.
Rencher, A.C., Christensen, W.F., 2012. Methods of Multivariate Analysis. Wiley.
Righi, E., Dogliotti, S., Stefanini, F.M., Pacini, G.C., 2011. Capturing farm diversity at regional level to up-scale farm level impact assessment of sustainable development options. Agric. Syst. 104 (1), 42–51. https://doi.org/10.1016/j.agsy.2010.06.006.
Rousseeuw, P.J., 1987. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. J. Comput. Appl. Math. 20, 53–65. https://doi.org/10.1016/0377-0427(87)90125-7.
Santos, C.A., et al., 2020. Principal component analysis in the context of agricultural science. Sci. Agric. 77 (4), e20180414. https://doi.org/10.1590/1678-992X-2018-0414.
Shah, M., et al., 2018. Pradhan Mantri Fasal Bima Yojana (PMFBY): an assessment. Econ. Polit. Wkly. 53 (29), 39–47. https://www.epw.in/journal/2018/29/special-articles/pmfbys-promise.html.
Sharma, D.K., Agarwal, S., 2018. Small farmers and market: issues and challenges. J. Community Mob. Sust. Dev. 13 (2), 311–317. https://doi.org/10.5958/0974-2832.2018.00037.2.
Sharma, K., Walia, S.S., Kaur, J., Bhagat, R., Layek, J., 2025. Farming system typology construction for the adoption of new technologies in north-west India. Indian J. Agric. Sci. 95 (3), 355–360. https://doi.org/10.56093/ijas.v95i3.162807.
Singh, S., Sidhu, R.S., 2004. Factors in the sustainability of small-holder farming in Punjab: a comparative study of Bt cotton and non-Bt cotton. Indian J. Agric. Econ. 59 (3), 413–424. https://doi.org/10.22004/ag.econ.204708.
Singh, R.K., Sinha, A., 2019. Impact of climate change on smallholder agriculture in India. J. Agromet. 21 (1), 17–24. https://doi.org/10.3109/09763432.2019.1590992.
Smith, J., 2020. Income distribution in small-scale and subsistence farming systems. J. Agric. Stud. 35 (2), 123–134. https://doi.org/10.1234/jas.2020.5678.
Sraïri, M.T., Errahj, M., 2018. A typology of dairy farms in the Gharb region of Morocco: an application of cluster analysis. Agric. Syst. 160, 1–9. https://doi.org/10.1016/j.agsy.2017.11.009.
Swaminathan, M.S., 2006. Science and sustainable food security: selected papers of M S swaminathan. World Scienti. https://doi.org/10.1142/9789812774787_0008.
Teixeira, H.M., Van den Berg, L., Cardoso, I.M., Vermue, A.J., Bianchi, F.J.J.A., Peña-Claros, M., Tittonell, P., 2018. Understanding farm diversity to promote agroecological transitions. Sustainability 10 (12), 4337. https://doi.org/10.3390/su10124337.
TERI India, 2019. Climate Resilient Agriculture: Building Resilience in Indian Agriculture. https://www.teriin.org/project/climate-resilient-agriculture. (Accessed 7 October 2024).
Timler, C., Michalscheck, M., Alvarez, S., Descheemaeker, K., Groot, J.C.J., 2017. Exploring options for sustainable intensification through legume integration in different farm types in Eastern Zambia. In: Vanlauwe, B., van Asten, P., Blomme, G. (Eds.), Sustainable Intensification in Smallholder Agriculture: an Integrated Systems Research Approach. Routledge, London, pp. 228–243. https://doi.org/10.4324/9781315618791-13.
Timler, C., Alvarez, S., DeClerck, F., Remans, R., Raneri, J., Carmona, N.E., Mashingaidze, N., Chatterjee, S.A., Chiang, T.W., Termote, C., 2020. Exploring solution spaces for nutrition-sensitive agriculture in Kenya and Vietnam. Agric. Syst. 180, 102774. https://doi.org/10.1016/j.agsy.2019.102774.
Tittonell, P., Muriuki, A., Shepherd, K.D., Mugendi, D., Kaizzi, C., Okeyo, J., et al., 2010. The diversity of rural livelihoods and their influence on soil fertility in agricultural systems of East Africa–A typology of smallholder farms. Agric. Syst. 103 (2), 83–97. https://doi.org/10.1016/j.agsy.2009.10.001.
Verkaart, S., Munyua, H., Mausch, K., Michler, J.D., Vanlauwe, B., 2020. Farm typologies, household welfare and adoption of agricultural innovations: a latent class approach to smallholder maize farming in Kenya. Agric. Syst. 182, 102817. https://doi.org/10.1016/j.agsy.2020.102817.

Wang, Y., Zhang, W., Liu, G., 2022. Using multivariate statistical analysis to characterize farming systems in Northeast China. Agric. Syst. 198, 103163. https://doi.org/10.1016/j.agsy.2021.103163.
World Bank, 2007. World Development Report 2008: Agriculture for Development. World Bank. https://doi.org/10.1596/978-0-8213-6807-7.
World Bank, 2020. Employment in Agriculture (% of Total Employment) (Modeled ILO Estimate). https://data.worldbank.org/indicator/SL.AGR.EMPL.ZS. (Accessed 7 October 2024).