



# Farm Typology for Targeting Extension Interventions Among Smallholders in Tribal Villages in Jharkhand State of India

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The highly heterogeneous and complex farm holdings operated by the smallholders in developing countries are often deprived of optimum production and profitability. The farming systems in the state of Jharkhand, India, are heterogeneous due to biophysical (e.g., climatic conditions, fertilizer status, elevation, etc.) and socio-economic (investment potential, production goals, income preferences) factors. The extension interventions to reach the smallholders often face the one-size-fits-all approach making farming less attractive with diminished potential. There is a need to understand the diversity of the farms to classify them into different homogenous groups after studying the nature and characteristics of the farm and operators on the farms. In the current study, twenty-one different variables related to socio-economic, biophysical and geospatial features of the farms from 394 farm households were used for the analysis using Principal Component Analysis to identify six principal components explaining 73.07% of the total variability in the dataset. The first six factors were further analyzed using Euclidean Distance as distance measure and Ward's technique as agglomerative clustering to form four clusters that were found to represent the farm households in the three villages. The four farm types identified were, Type 1. Large farm household with a diversification of crops and intensification of labour (22%), Type 2. Small farm households with major income from livestock (9%), Type 3. Small farm households with diversified cropping system and income from other sources (17%), and Type 4. Small farm households with monocropping dominated by senior farmers with an additional source of income (51%). The validation of the clusters was undertaken through qualitative methods such as focused group discussions and participatory workshops. The findings back up previous research that showed a positive association between farmer categorization and mathematical classification. The study offers a verifiable scientific methodology that could help scale agricultural technologies by forming a specific cluster of farmers based on their characteristics. The technologies applied to various farm types would be helpful to the extension system to target the interventions among the precise members of the identified farm types. Thus, the study suggests the farming system typology based on socio-economic,

biophysical and geospatial factors for targeted farming systems interventions among smallholders.

**Keywords:** farm typology, extension, tribal, smallholders, classification

## 1 INTRODUCTION

A geographically and demographically diverse country like India, dominated by smallholder farms (Priyadarshini and Abhilash, 2020), requires continued research towards understanding farmers' needs, capabilities, available resources, and risk appetite (Robert et al., 2017; Antony et al., 2020). Targeting extension interventions for such heterogeneous farming systems is challenging in low-and medium-income countries due to inadequate data and classification mechanisms (Daskalopoulou and Petrou, 2002; Chatterjee et al., 2015). The development of farm typologies could be an essential step in capturing the diversity associated with the farms (Priegnitz et al., 2019; Bisht et al., 2020), along with providing due consideration to the adoption of new technologies by the farming community (Bozeman, 2000; Amadu et al., 2020). Such typologies can also be helpful in the development of robust policy initiatives for the developing countries and provide better advisory support for the farmers (Ruben and Pender, 2004).

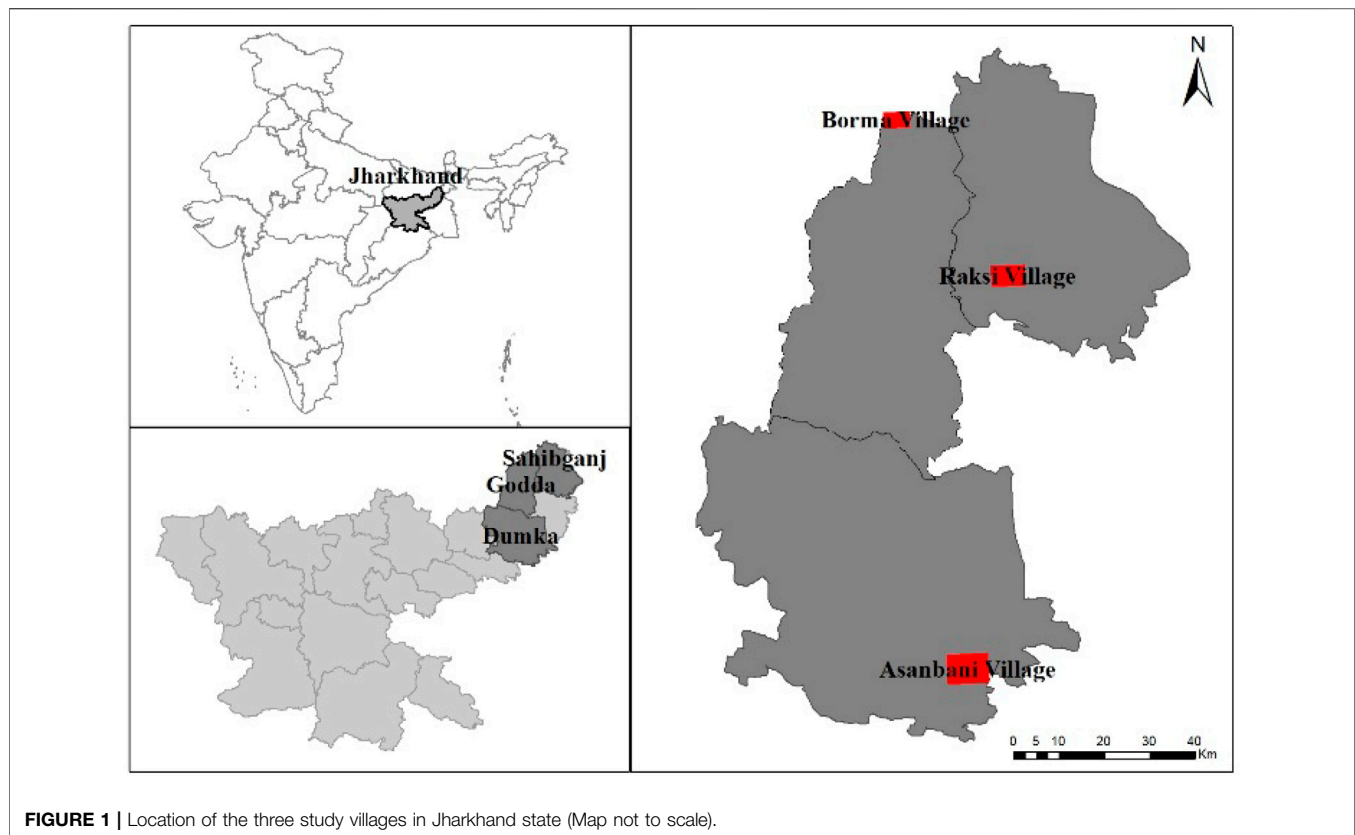
The rapid adoption of newly developed agricultural technologies would result in better returns on investment resulting in sustainable livelihoods for the rural populace. However, many farm technologies are rejected mainly by heterogeneous smallholder farmers in developing countries since there is a need for specific technological solutions suiting their context (Anugwa et al., 2021; Sinha et al., 2021). For example, the smallholder farmers in Jharkhand, India (the study locale of the current research) are primarily dependent on double cropping of rice and wheat or intercropping of vegetables with mango orchards (Gupta, 2020; Sharma et al., 2020), which has led to the increase in risk associated with farming and threatening the farms' sustainability over the years (Hammond et al., 2020; Kilwinger et al., 2021). The extreme dependence on income from crops and little thrust on value proposition is also responsible for the youth to look for opportunities other than agriculture (Brooks, 2018; Som et al., 2018). The efficiency of agricultural research and extension system necessitates the adoption of new technologies by the farming community (Bozeman, 2000) without considering factors such as agroecology, resource endowment, and source of income (Ehsan Elahi et al., 2021; Elahi et al., 2021). The identification and characterization of farming systems simplify the diverse farm types, helping target extension intervention and informed advisory and policy support (Köbrich et al., 2003; Sarker et al., 2021).

Previous studies on farm typologies have taken factors such as cash availability and labour requirement (Tittone et al., 2007), gender-based decisions (Tavener et al., 2019), ecological diversity (Kansiime et al., 2021), and management practices (Zhang et al., 2021) into consideration for capturing the diversity associated with the farming systems. The farm

typologies have been extensively used to study rice-based cropping systems (Siddique et al., 2022), greenhouse gas emissions (Musafiri et al., 2020), climate-smart agricultural practices (Mujeyi et al., 2021) and cattle production systems (Zoma-Traoré et al., 2020). These typologies are sometimes representative of the crop understudy like rubber-based farming (Sankalpa et al., 2021), rice-wheat cropping system (Toorop et al., 2020), and addressing gaps in maize productivity (Villarreal et al., 2020). However, a majority of the researches on farm typologies related to smallholders have focused on socio-economic and agroecological factors (Kmocho et al., 2018), land-elevation (Rahman, 2018), physical and biological environment (Escobar et al., 2019) for the classification of farms. The gap in the existing researches was bridged by the current study in making use of both biophysical (e.g., climatic conditions, fertilizer status, elevation, etc.) and socio-economic (investment potential, production goals, and income preferences) factors for identifying the farming typology of tribal smallholders in the Jharkhand state of India. Also, the spatial analysis using geographic information systems (GIS) to assess the impact of increased construction and farm buildings was explored over a period of 5 years to identify relevant variables for the study. Finally, different variables from the above factors that outline farm typologies were decided based on the research objectives. The advantage of the integration of GIS into the typology research is to take advantage of the strengths of all partners in variable identification, such as quantitative identification and characterization methods based on expert knowledge (Righi et al., 2011) and geospatial and temporal data based on GIS data of the identified land parcel.

The research addressed two central research questions. First, does the development of farm typologies help in the apt classification of farming systems in developing countries? Second, can participatory techniques account for the successful validation of the farm typologies created through statistical analysis? The two objectives of the study were to identify the farm typologies using the current GIS-oriented methodology to determine the farm typologies of the tribal farm households. The second objective is to study the integration of participatory approaches to validate farm typologies for the efficient targeting of extension interventions. This study attempts to capture the diversity and complexity associated with the smallholder tribal farmers mainly operating on subsistence farming. To do this, we use different robust variables obtained through biophysical, socioeconomic, and GIS domains (Anyimah et al., 2021) that could help capture the diversity associated with the farms in a more precise manner. As a result, we may design and build a "recommendation domain" for each set of reasonably homogenous agricultural systems obtained from our study.

Further, the unique constraints faced by each of the identified farm types are matched with the inventory of prospective



**FIGURE 1** | Location of the three study villages in Jharkhand state (Map not to scale).

technologies for sustainable intensification of smallholder farming systems using participatory methods. This would result in sound policy interventions and advisory mechanisms for enhancing the adoption of agricultural technologies suited to the region. In this way, the typologies could also be used to formulate policy initiatives for similar less-privileged areas. The study is novel in terms of developing farm typologies for the tribal regions operating on subsistence agriculture and evaluation of the developed typologies by the group of farmers themselves. Thus, this study adds to the body of knowledge on operationalization of farm household typologies for targeting extension interventions among smallholder farmers.

The paper is divided into three major sections. The first provides information on the locale of the study, the variables selected for the research and the use of different multivariate statistics. The second section examines the construction of different typologies for the classification and validation tools. The third section discusses the concludes the study along with providing limitations of the study and recommendations for future research.

## 2 MATERIALS AND METHODS

### 2.1 Study Area

The agro-climatic zone of Jharkhand comprises three zones (Zone-IV, V, and VI). Three different villages from three different districts in Zone IV (Central and northeastern

plateau) were purposively selected for the study based on total enumerative sampling. All the farming households from the selected villages were chosen for the study. The selected villages were Borma (25.2098° N, 87.3538° E) in Godda district, Asanbani (24.3215° N, 87.1809° E) in Dumka district, and Raksi (24.7720° N, 87.6717° E) in Sahibganj district of Jharkhand (Figure 1).

The villages under consideration were primarily rural, with an average distance from the nearest town/city of roughly 40 km. Almost 94 percent of the village's households relied on agriculture and related occupations for survival. During the pre-monsoon, the groundwater table in the villages ranges from 5 to 7.5 m, while during the monsoon, it ranges from 12 to 18 m. In all of the settlements, the tube well is the major source of irrigation.

One village from each of the districts was randomly selected as a representative farming system of the locale. The farming practice prevalent in the villages were a mix of subsistence farming and family farming. All the farming households were taken under consideration from each village, resulting in a sample of 394 farm households. In order to offer extensive statistical coverage over geography and time, a thorough enumeration-based survey with the established interview schedule was undertaken in the three villages. The data collection was completed from January to June 2019 and included all of the agricultural households in the communities that were identified. Based on the questionnaire, 26 surveyed bio-physical and socioeconomic variables from the three villages were subjected to careful examination to determine the missing data and identify

possible outliers. Further, boxplots were used to detect outliers that were eliminated later to improve the multivariate analysis. The data refinement so performed was consistent with (Kuivanen et al., 2016a; Hammond et al., 2020).

Finally, 21 surveyed bio-physical and socioeconomic variables were selected from the three villages that were found suitable for further analysis, development of typologies, and distinct clusters as mentioned in **Table 1**. The survey was performed following their relevant guidelines and regulations approved by the advisory committee for doctoral study at Bidhan Chandra Krishi Viswavidyalaya, India. Strict adherence was made to the Code of Ethics of the International Sociological Association (ISA) (Head, 2009) to formulate and execute the schedule.

## 2.2 Typology Construction

### 2.2.1 Selection of Variables

The socio-personal, economic, and biophysical characteristics pertaining to the farming household as well as the operational agricultural land were meticulously recorded. Further, the multi-temporal land use/land cover (LULC) mapping and change detection analysis was carried out for the study villages to categorize five distinct classes which are fallow land, agriculture, forest, buildup area and waterbody for a period of 5 years from the year 2010 to the year 2015 with the help of GIS data obtained from Bhuvan Geoportal of ISRO (2019) and Landsat platforms Geological Survey (U.S.) and EROS Data Center (2019)). Previously, the use of remote sensing data acquired at high spatial and temporal resolution for the classification of rice cropping systems and develop a farm typology to classify the main crop practices at the territory level was performed with high levels of accuracy (Courault et al., 2020).

To overcome the effects of multicollinearity, the 26 variables were subjected to correlation analysis. Normally, we use VIF (Variance inflation factor) to handle multicollinearity in any dataset. Multicollinearity occurs when two or more independent variables are highly correlated with one another. Hence, we use VIF to find those variables and remove them, which is also a part of data-preprocessing. Therefore, in data preprocessing, we checked for multicollinearity between independent 26 variables using VIF and manually removed the correlated variables one by one. A VIF value of 1 means no correlation between the independent variable and other variables. The VIF value exceeding 5 or 10 indicates high multicollinearity between this independent variable and the others. In the current study, we kept a VIF threshold of 5, and excluded all variables which have VIF value above 5. The significantly correlated variables were identified, and those explaining greater diversity were selected. The data was further scrutinized for the identification of missing values and outliers. Calculated boxplots were used as a part of data pre-processing as it helps to visualize the distribution of quantitative values in a field and detect outliers. Finally, 21 variables were retained for further analysis based on such analysis (**Table 2**).

### 2.2.2 Multivariate Analysis

The principal component analysis (PCA) and cluster analysis are two multivariate statistical approaches used to identify typologies (CA) in our research. The analysis was performed in SPSS Ver. 23.0 (Corp, 2016) and the visualization was executed in R, version 3.1.0, ade4 package (Dray and Dufour, 2007).

### 2.2.3 Principal Component Analysis

PCA is a dimensionality reduction technique that helps in increasing the interpretability of the variables and minimizes information loss. It condenses the information from the interdependent variables and converts it into a small set of factors (Jolliffe and Cadima, 2016). For the PCA analysis, a total of 21 distinct variables relating to the farms' socioeconomic and biophysical characteristics were considered. In addition to family labour, the study looked at revenue from other sources (off-source income). The increasing cost of labour and less availability during the peak season of the crop is found to be a matter of concern in the study villages. As such, the farmers are utilizing more family labour and getting engaged in family farming practices. Also, the diversification of income to sources other than agriculture was also found to be an essential factor for classification (Kessler et al., 1998; Fernandez-Cornejo et al., 2005; Paul and Nehring, 2005).

### 2.2.4 Cluster Analysis

Using Euclidean Distance as a distance measure and Ward's approach as agglomerative clustering, the PCA result in the form of a smaller dataset was employed for further analysis (Gebauer, 1987; Hair et al., 1987; Gorton et al., 2008; Sutherland et al., 2011). The schedule developed from this analysis is called agglomeration schedule, which illustrates the analysis sequence and the coefficients. The schedule is instrumental to the identification of an appropriate number of clusters that fits the dataset suitably. A closer observation of the agglomeration schedule and the Scree diagram suggests the appropriate number of clusters.

### 2.2.5 Validation of Farm Types

The validation of the clusters developed from the typology-based study and fitting of the agricultural technologies with the clusters was undertaken through qualitative methods. The assessment was necessary to find the best fit for the extension and farmers' technology developed from our mathematical model based on the farmers' socioeconomic and biophysical parameters, with the identified typologies by the practicing farmers themselves. The detailed methodology is summarized in a flowchart (**Figure 2**).

## 3 RESULTS AND DISCUSSION

### 3.1 Characterization of Farming System

**Principal Component Analysis:** The first six main components with an eigenvalue larger than one account for 73.07 per cent of the dataset's overall variability. The six components were used for further analysis. Further, the scree plot (plot of the eigenvalues of factors or principal components in an analysis)

**TABLE 1** | Summary statistics of surveyed variables from the three villages for characterization of farm household.

Code	Description	Unit	Borma				Raksi				Asanbani			
			Min	Max	Mean	Median	Min	Max	Mean	Median	Min	Max	Mean	Median
hhsz	Number of members in the household	Number	1	25	7.12	6	2	13	5.54	5	2	12	5.84	5.50
Agefarmer	Age of the primary farmer	Years	27	92	54.98	55.50	22	27	45.72	43	30	76	53.26	55
Eduyear	Number of years of education of primary farmer	Years	5	17	9.65	10	0	30	12.98	12	8	40	13.30	12
Eduindex	Number of years of education of all members of the household	—	1.45	4	2.45	2.38	0.67	3	1.50	1.40	1	3	1.59	1.50
Yrsinfrm	Number of years in farming	Years	5	55	29.38	30	0	60	23.90	20	0	50	27.07	30
Totalarea	Total area of farming	Bigha <sup>a</sup>	0	18	4.18	3	0	30	3.14	2	1	10	2.11	2
Ownedar	Owned area of farmland	Bigha <sup>a</sup>	0	16	3.75	3	0	40	2.91	2	0	10	2	2
Cattle	Number of cattle owned	Number	0	5	0.75	1	0	7	2.63	2	0	4	1.23	2
Smallrum	Number of small ruminants owned	Number	1	10	3.34	2	0	10	4.03	4	2	10	4.53	4
Cropinc	Income from cropping practices	Rupees	1,600	88,000	18,639.07	13,200	0	90,000	7,591.07	5,000	1800	38,000	5,159.61	3,500
Animinc	Income from animal husbandry	Rupees	0	60,000	11,238.14	10,000	0	40,000	9,701.78	10,000	2000	60,000	10,382.69	9,000
Offsour	Income from sources other than agriculture	Rupees	0	200,000	40,576.27	20,000	0	200,000	28,675	20,000	5,000	144,000	43,500	25,500
pensioninc	Income from pension	Rupees	0	7,200	1,037.28	0	0	14,400	771.42	0	0	14,400	1,384.61	0
rentedlab	Number of days rented labour employed in a year	Number	20	365	140.16	129.50	0	300	66.38	50	0	400	54.80	30
Famlab	Number of days family labour employed in a year	Number	300	365	353.60	365	0	220	70.12	70	0	100	50.96	50
totalanday	Total of days of rented labour and family labour	Number	320	720	493.51	485	0	500	137.65	105	50	500	106.73	100
CDI	Crop Diversification index	—	0.48	0.82	0.62	0.66	0	0.84	0.38	0.37	0.18	0.48	0.25	0.18
SCC	System cost of cultivation	—	1,000	40,000	9,204.23	6,900	1,200	40,000	9,548.21	8,200	2,900	34,500	7,861.53	6,200
SGR	System gross return	—	1,600	88,000	18,850.93	13,200	2000	98,000	17,292.86	15,000	4,600	70,000	15,542.31	12,500
SNR	System net return	—	600	50,000	9,646.69	6,450	700	58,000	7,744.64	6,700	1700	35,500	7,680.76	5,800
CBR	Cost benefit ratio	—	1.60	2.50	1.95	1.93	1.31	3.07	1.77	1.79	1.54	2.16	1.93	1.97

<sup>a</sup>1 bigha = 0.26 ha.

**TABLE 2** | Sampling scheme.

State name	District name	Block name	Village name	No. of respondents	Total sample size	Selection procedure
Jharkhand	Godda	Meherma	Borma	118	394	The three districts were selected randomly from the Zone IV Agro-climatic zone of Jharkhand. The three villages were selected purposively from each of the district whereas all the respondents (farming households) have been selected through total enumerative sampling
	Dumka	Dumka	Asanbani	224		
	Sahibganj	Berhait	Raksi	52		

is used to determine the number of factors to retain in exploratory factor analysis. A scree plot (**Figure 2A**) displays the eigenvalues in a downward curve, ordering the eigen values from largest to smallest. The “elbow” of the graph where the eigenvalues seem to level off, which is reached after the sixth factor and the factors or components to the left of this point is retained as significant.

Further, we define each component by observing the strongly associated variables in each of the components. The first component, which is connected with crop revenue, crop diversification index, system cost of cultivation, gross system returns, and system net return, explains 30.21 percent of the variation in the dataset. As a result, the component indicates crop income and high-resource farmers who generate higher money. The second component accounts for 15.92 percent of the variation and is linked to the educational index, total hired and family labour on the farm, livestock revenue, and crop diversification. This component explains the revenue from cattle, the intensification of farm labour, and educational achievement. The third primary component accounts for 9.74 percent of the variation and is linked to the farmer’s age, the number of years committed to farming, and government pension income. The fourth component accounts for 6.29 percent of the variation and is linked to the farmer’s overall land holdings and other sources of income (off-source income). The fifth factor accounts for 5.55 percent of the variation and is linked to the size of the household and the number of years the farmer has been educated. The last factor accounts for 5.33 percent of the variation and is linked to revenue from animals and small ruminants.

“Income from crop and net income from the system” (PC1), “crop diversification and intensification of labour” (PC2), “experience in farming and income from pension” (PC3), “off-source income and total operational farm area” (PC4), “education and household size” (PC5), and “income from livestock” (PC6) could be the names for the six main components (PC6). It is also worth noting that the first two components explain 46.13% variance in the dataset, which is higher than the variance (26.91%) explained by the other four components combined. The scree plot and the correlation plot are illustrated in **Figures 3A,B**.

### 3.2 Cluster Analysis

The schedule developed from this analysis is called the agglomeration schedule, which illustrates the study sequence and the coefficients. The schedule is instrumental to the identification of an appropriate number of clusters that fits the

dataset suitably. A closer observation of the agglomeration schedule and the Scree diagram suggests that the appropriate clusters should be four in number. It was further matched with the variables collected and classification of the three villages to provide an apt classification. The farm households in the three villages were found to be represented by the four clusters that had been constructed.

The four clusters were also used to create final clusters using the k-means clustering approach. The four clusters could also be identified from the dendrogram in **Figure 4A** and cluster silhouette plot in **Figure 4B**, which shows the separation distance between the resulting clusters, providing an effective visualization of the resulting results clusters. The distribution of farm households in different clusters is further visualized in **Figure 4C**.

A one-way analysis of variance for each of the major components was used to test the cluster analysis’ veracity (equality of group mean scores). The results of the one-way analysis of variance performed with the four clusters are presented in **Table 3**. The lower *p*-value denotes the distinctness of the principal component under observation. The *p*-value represents that all the factors, namely PC1 (Income from crop and net income from the system), PC2 (Crop diversification and intensification of labour), PC3 (Experience in farming and income from the pension), PC4 (Off source income and total operational farm area), PC5 (Education and household size), and PC6 (Income from livestock) have a *p*-value nearing to 0.00 ( $p = 0.000$  for all the factors). Thus, it can be concluded that the components are significant in differentiating various clusters. The results are in congruence with the study on typology (Goswami et al., 2014). The last stage involved aggregating all data collected at field level to the farm level using open source QGIS geospatial analysis software (Flenniken et al., 2020). The most important variables obtained from remote sensing data were taken into account.

### 3.3 Characterization of Identified Farm Types in Different Clusters

The characteristics of the four clusters concerning the socioeconomic variables and biophysical features of the farming systems is presented in **Table 4**.

Type 1. Large farm household with a diversification of crops and intensification of labour (22% of sampled farms).

The first type is represented by large households with greater age of the main farmer of the household. The

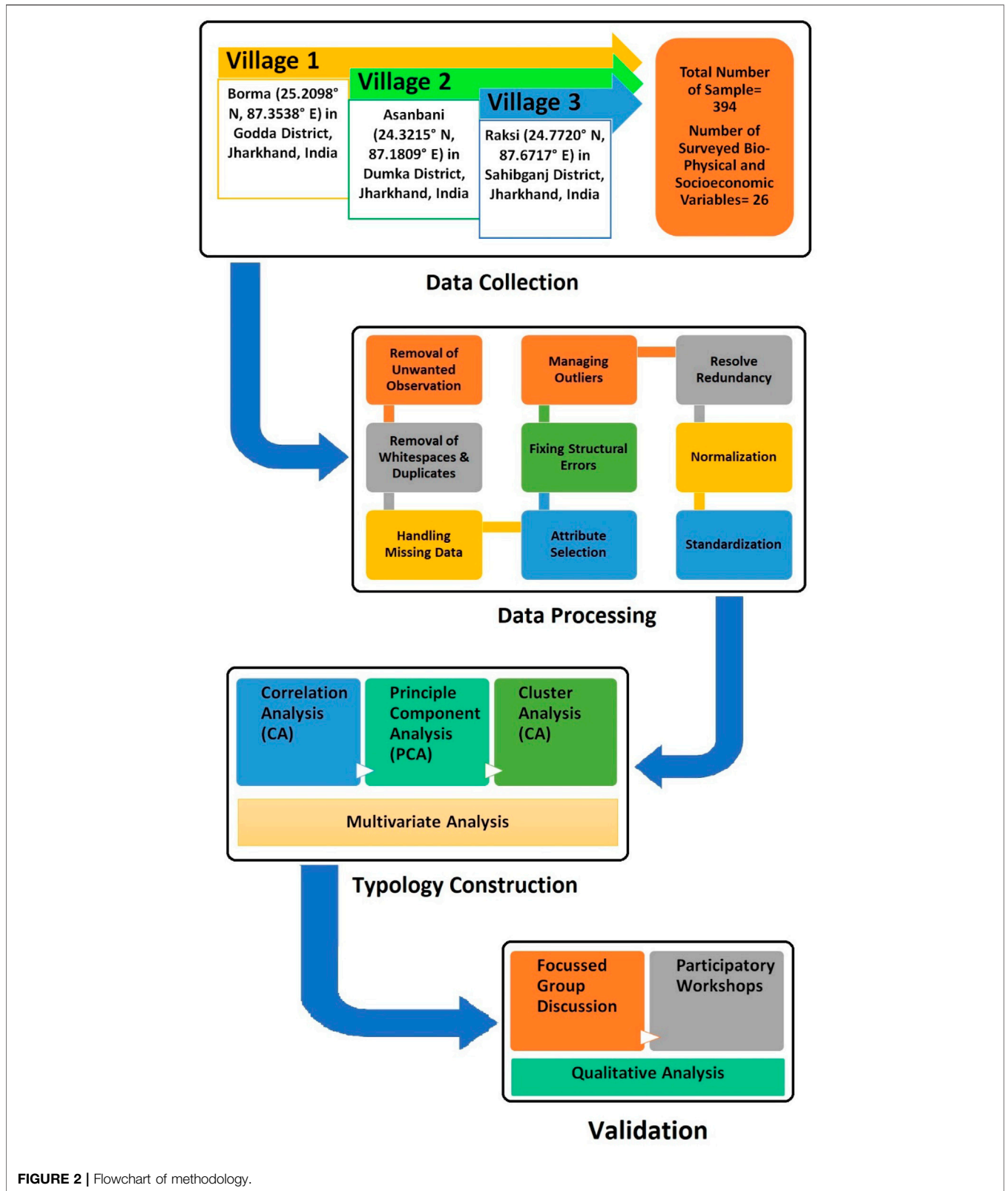
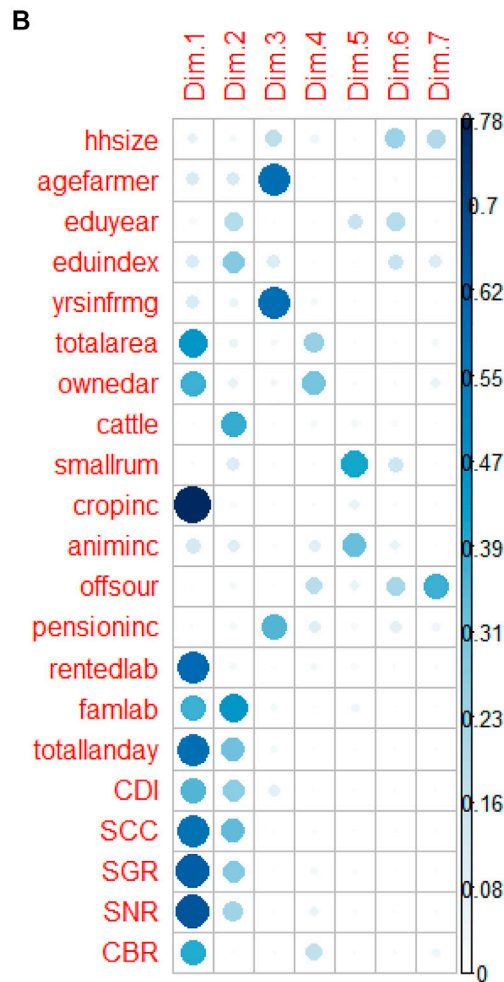
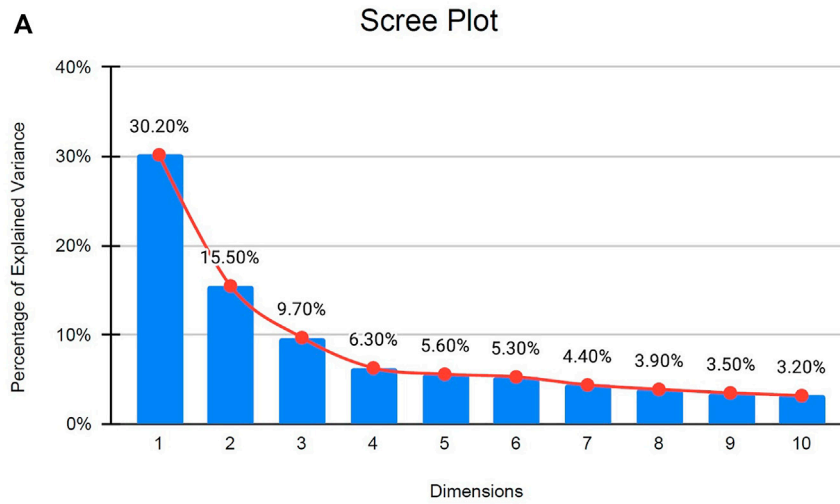
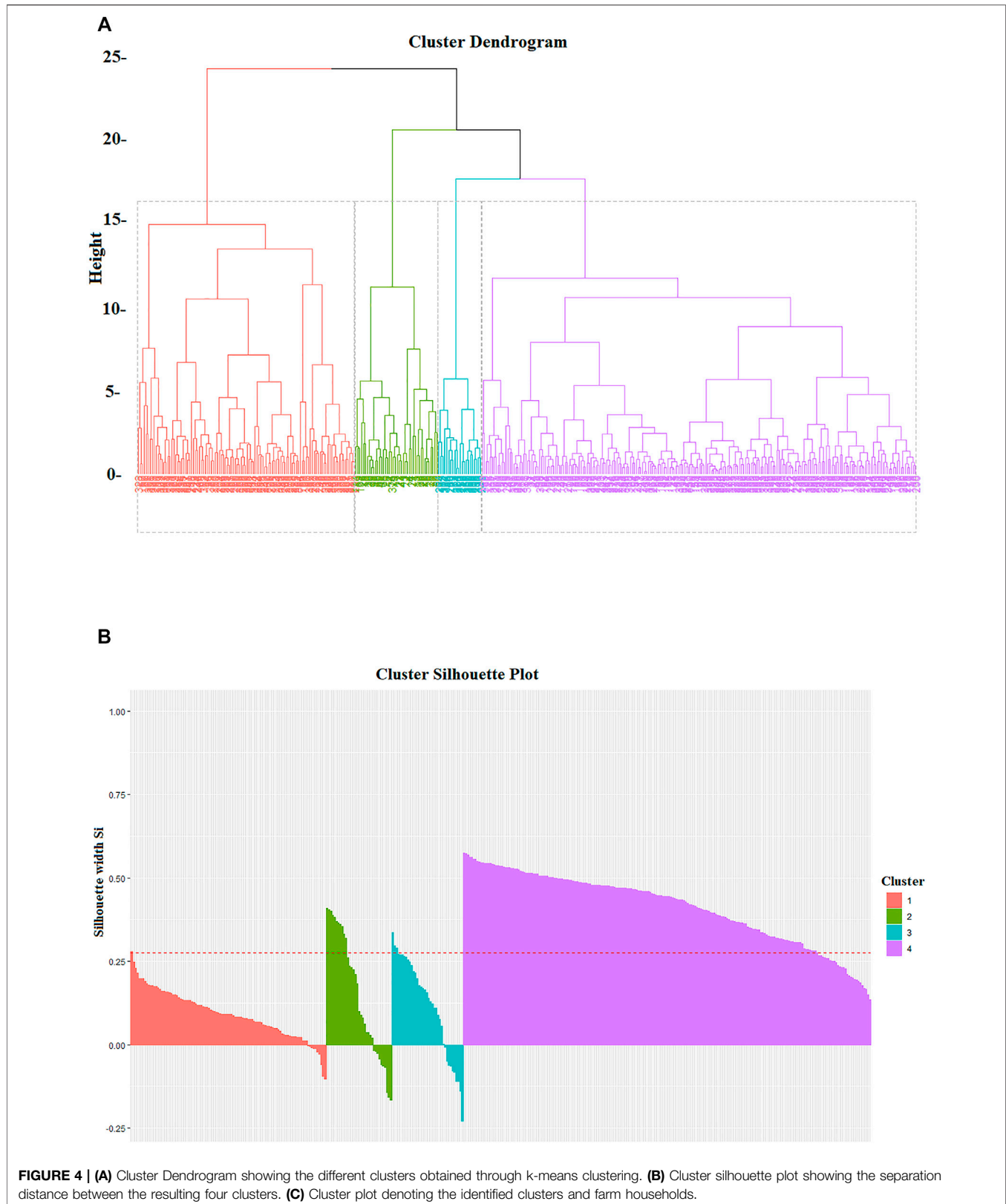


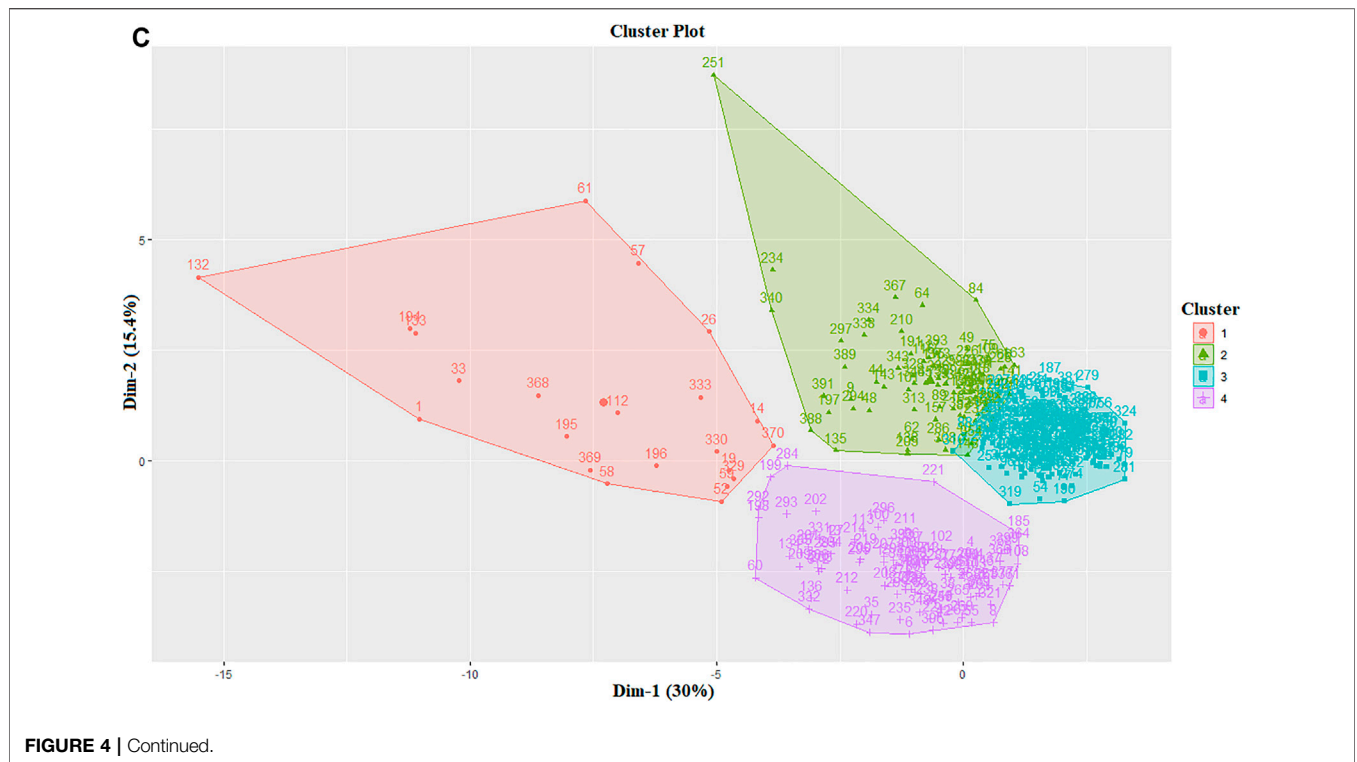
FIGURE 2 | Flowchart of methodology.



**FIGURE 3** | Output of PCA result. **(A)** Scree plot showing the cumulative variance explained by each principal component in the study. **(B)** The correlation plot of the variables and components







**TABLE 3 |** One-way analysis of variance of factor scores across four identified clusters.

Principal components	Cluster		Error		F	Sig
	Mean square	Df	Mean square	Df		
PC1(Income from crop and net income from the system)	30.855	3	0.422	390	73.073	0.000
PC2(Crop diversification and intensification of labour)	88.507	3	0.308	390	286.984	0.000
PC3(Experience in farming and income from pension)	3.779	3	0.931	390	4.057	0.007
PC4(Off source income and total operational farm area)	17.715	3	0.475	390	37.270	0.000
PC5(Education and household size)	7.356	3	0.841	390	8.752	0.000
PC6(Income from livestock)	69.324	3	0.391	390	177.193	0.000

income obtained from cropping practices and other sources is highest for this cluster. The use of rented labour and family labour in this cluster is found to be the highest which may be because of the presence of bigger landholding. The economic indicators indicate that this group has the largest net returns from the farming system and the maximum cost-benefit ratio.

The skills of these farmers could further be diversified in relation to poultry management through training and education. They could be provided with bank credit, taking into account their economic wellbeing and the social conditions in which they live (Guèye, 2002). With further development, poultry enterprises could deploy the family labour better with enhanced income generating opportunities. These farmers could also partner with contract farming agencies to produce wheat and maize in bulk since both commodities are widely grown in the villages but fail to fetch the minimum support price in the local market (Le Ngoc, 2018).

Type 2. Small farm households with major income from livestock (9% of sampled farms).

In the second type, the members had relatively smaller land, smaller family size, and less income generation capacity from the cropping systems (Column 2). This cluster invests the maximum among the other groups in terms of the rearing of livestock, providing additional income. These households are found to achieve lesser net returns from the cropping system and less cost-benefit ratio. Also, they are relatively young farmers who could be engaged in more remunerative aspects of farming to further increase the cost-benefit ratio. These farmers could be provided support to grow cash crops on a larger scale for meeting the demand from the market. They could further be provided farm credit, market information, and various crop management technologies to increase the yield further from small parcels of land (Mariyono, 2018). The availability of extension support in

**TABLE 4 |** Characteristics of identified clusters of farm households and *p*-value of one-way analysis of variance (equality of group mean) for variables used in the characterization of farm types.

	Cluster				Cluster		Error		F	Sig
	C1 (88)	C2 (38)	C3 (67)	C4 (201)	Mean square	Df	Mean square	Df		
Hhsize	9.00	6.24	5.87	6.18	27.396	3	6.340	390	4.321	0.005
Agefarmer	60.38	49.72	48.64	51.73	451.985	3	154.089	390	2.933	0.033
Eduyear	12.75	11.80	12.02	12.47	5.933	3	14.420	390	0.411	0.745
eduindex	1.89	1.89	1.73	2.00	1.269	3	0.464	390	2.732	0.044
yrsinfrmng	35.63	27.23	24.85	27.69	446.237	3	113.733	390	3.924	0.009
totalarea <sup>a</sup>	9.56	5.71	2.29	2.81	374.904	3	7.017	390	53.427	0.000
ownedar <sup>a</sup>	8.88	5.37	2.04	2.57	347.029	3	9.282	390	37.389	0.000
Cattle	1.13	2.53	1.78	1.24	21.545	3	2.658	390	8.107	0.000
smallrum	3.00	4.18	3.85	3.69	5.466	3	4.714	390	1.160	0.325
cropinc	75,087.50	18,951.58	5,193.25	10,877.11	15,696,608,112.458	3	54,512,929.579	390	287.943	0.000
animinc	15,437.50	15,534.74	7,948.78	10,766.67	1,394,405,001.259	3	50,978,483.981	390	27.353	0.000
offsour	25,000.00	21,210.53	23,244.72	123,111.11	133,987,990,484.776	3	337,406,005.252	390	397.112	0.000
pensioninc	998.00	985.26	936.59	960.00	2,419,651.903	3	8,807,277.180	390	0.275	0.844
rentedlab	223.75	132.11	60.28	113.13	183,079.961	3	3,927.978	390	46.609	0.000
Famlab	319.38	192.04	122.90	201.11	231,071.289	3	16,853.202	390	13.711	0.000
totallanday	543.13	324.84	184.04	314.24	812,427.817	3	27,671.957	390	29.359	0.000
CDI	0.67	0.50	0.41	0.46	0.333	3	0.023	390	14.726	0.000
SCC	32,562.50	15,698.95	6,080.08	8,580.00	3,596,845,305.427	3	14,597,418.059	390	246.403	0.000
SGR	76,087.50	30,130.53	10,963.98	16,399.33	17,726,175,318.655	3	57,246,585.640	390	309.646	0.000
SNR	43,525.00	14,431.58	4,883.90	7,819.33	5,459,728,253.261	3	15,745,212.812	390	346.755	0.000
CBR	2.34	1.92	1.80	1.88	1.044	3	0.025	390	42.162	0.000

<sup>a</sup>Area in bigha; 1 bigha = 0.26 ha.

Difference in mean among clusters found from Tukey's Range Test.

the villages is quite essential to streamline the functioning of this sector. Commercial dairy enterprises could also support them for collecting and marketing dairy products since the farm families have already integrated livestock in the farming systems.

Type 3. Small farm households with diversified cropping systems and income from other sources (17% of sampled farms).

The third type (Column 3) is featured by small landholding size, with less experienced farmers with relatively younger age among all four clusters. The rented labour and family labour use is minimum on these farms, and the net returns from the cropping practices was found minimum on these farms. The cost-benefit ratio of these farms was also the minimum among the other types. These farms mainly practice mono-cropping with little scope for diversification. The integration of the farming practices with livestock was also found to be lacking in these farm types. These farms were found to shift to other avenues for generating income than the farming practices, which is evident by the increased income source. These farms were mainly maintained for subsistence with little scope to sell the product further because of little production capacity. These farms additionally depend on social security schemes of the government to meet their food requirements. These farms could be sustained better with the integration of extension services for carrying on farming practices such as mushroom farming in their households. Mushroom farming requires little or no requirement of space. It could be successfully practiced in the

house itself. The marketing of the produce could be further enhanced through groups. Such type of farming would also result in meeting the nutritional requirement of the farm families. The limited landholding size of this cluster and underemployed populations with little potential to invest could lead to the viability of this farming to boost the rural economy and provide opportunities for smallholders to diversify further to increase their profits (Easin et al., 2017).

Type 4. Small farm households with monocropping dominated by senior farmers with an additional source of income (51% of sampled farms).

The last type comprises of 51.01% of the total farm households (Column IV). This is the group with most farm households. The cluster members had smaller landholding size (owned and total land), medium family size, and moderate farm diversification. The landholding of these farmers is highly fragmented, with little scope for collective farming on a large scale. These farmers greatly depend on other sources of income generation and are observed to have higher off-source income. The cost-benefit ratio of these majority farm households is comparable to the lowest among the other clusters. These farmers may be supported with intensive technologies on small farm holdings like integrated farming systems and fisheries. Such systems would need the support of extension machinery to sustain the interest and other requirements of the smallholders. The use of an integrated approach has assisted in the uptake of new technologies in several smallholder development projects around the world (McDonald et al.,

2019). Also, these farmers need enhanced marketing support to reach the market effectively with little wastages along the chain. The greater size of the family size could also be harnessed for agro-based enterprises on a small scale suitable to the interest of the villages like flour mills, vegetable processing facilities, pulp and pickle making etc.

The findings compare well with other studies on typologies conducted in Indo-Gangetic plains of India and coastal plains of Kerala in India. Kaur et al., 2021 and Innazent et al., 2022 used multidimensional analysis to describe farmer typologies in and around smallholder farmers in India. The current study even after using a different approach, compare to those of the study of the former. For example, “the small farm household with dependency on livestock” is similar to typology 2, “the resource endowed households oriented around fruits and vegetables” to typology 3, while “the resource endowed household with high levels of mechanization” can be equated with typology 4. Moreover, Goswami et al., 2014, also found similar results, which identified four predominant farm types oriented around differential income sources and resource-base. The extension agencies may be able to use the methodological approach used in the study as a decision-support tool for providing support to the farmer groups.

### 3.4 Validation of Farm Types

Qualitative methodologies were used to validate the four clusters produced from our typology-based study and to match agricultural technology to the clusters. The assessment was necessary to find the best fit for the extension and farmers’ technology developed from our mathematical model based on the farmers’ socioeconomic and biophysical parameters, with the identified typologies by the practicing farmers themselves. The results would also be helpful for the extension departments to generate and disseminate technologies based on the identified typologies from the villages. Incorporating a participatory research framework with typology identification might aid direct engagement with smallholders, perhaps increasing their acceptance of Decision Support Tools (DSTs). The information on different types of farmers may be used to establish a framework for discussing support systems that are more tailored to their requirements and emerging needs (Thar et al., 2021). Farmers in specific locations use their expertise to characterise and categorise their agricultural systems based on their experiences and social-cultural values in participatory approaches to farm classification (Nyambo et al., 2019). Differences in cultural attitudes on how women are tied to household chores, such as agriculture, might, for example, differ between research instances. However, statistical characterizations cannot capture these occurrences, and their explanations are often inadequate (Kuivaniemi et al., 2016b). As a result, it is widely accepted that scientific knowledge derived from statistical methods may be understood using local knowledge of farmers of the region (Kapalanga, 2008).

The qualitative methods aim to provide an in-depth and interpreted understanding of the current situation of the people concerning social and material circumstances along with due consideration to their experiences and varied

perspectives (Ritchie et al., 2013). This approach was found suitable for this study to understand the farmers’ assessment of the typologies in their context, which would be beneficial to promote the necessary farming technologies suited to their situations based on the socioeconomic factors applicable at the household and farm level. This would help identify the critical constraints in our mathematical approach towards the development of farm typologies and provide a way to the technology adoption and dissemination process. The qualitative data would help to understand whether the farmers’ rationale in identifying farmers and technology recommendations is the same as that claimed in the study, and if that is not the case, what is the reason behind it. The qualitative data is equally helpful to identify the social and regional factors affecting different cultural situations of the farm households, which is challenging to identify by the researcher since they are an outsider to the complex farming situations underplay in the rural environments. The qualitative interviews and focus group conversations with persons on the receiving end of communications may offer in-depth understandings of how people interpret populist and understand populist messages that might provide valuable insight into the shared perspectives and opinions (Hameleers, 2018).

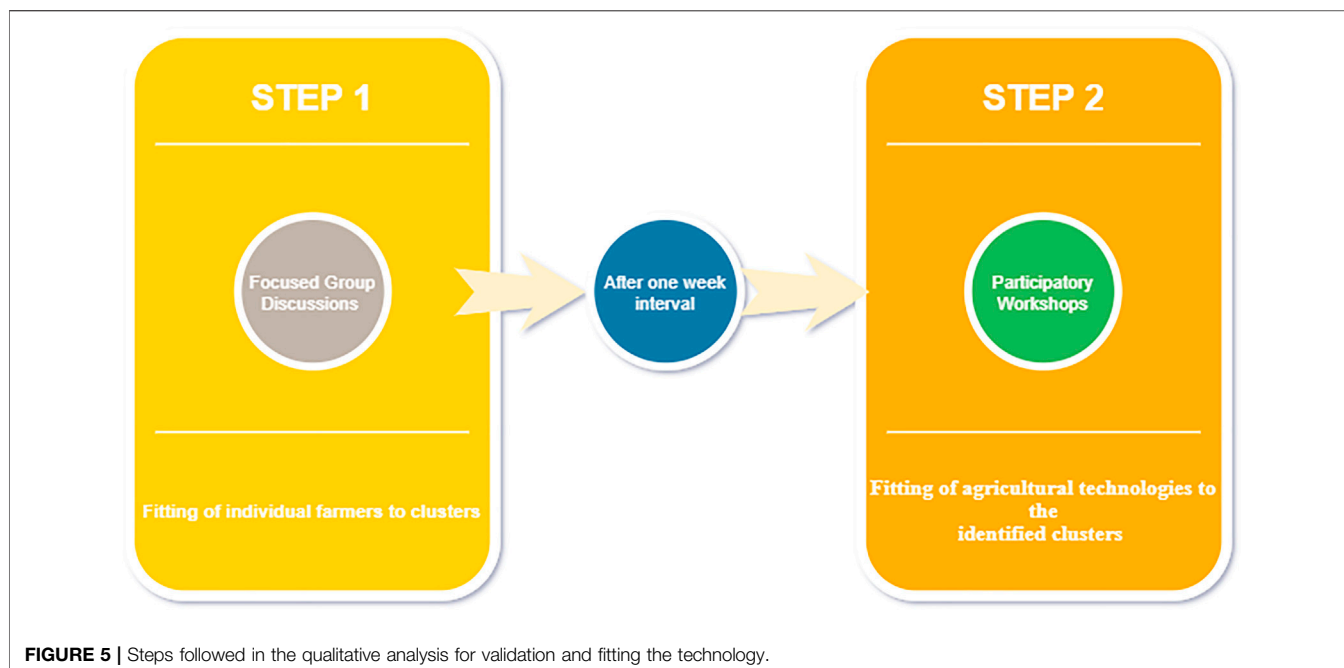
This is useful to the researcher and acts as valuable feedback to customize the technology basket better for the farmers. Focused group discussions (FGD) and participatory workshops were employed as qualitative tools in this study. The steps followed in the study is depicted in **Figure 5**.

### 3.5 Focused Group Discussions

The focus groups were conducted with eight key informants from each of the three villages, all of whom had at least 20 years of farming experience. It was ascertained that there is at least one key informant from each of the clusters obtained in our study. The FGDs also allowed open discussions among the participating farmers. The study also employed a local youth from the village who acted as a facilitator to clarify the questions and identify the situations in the local dialect. The group size for the FGDs was established with due consideration to the empirical data regarding adequate size (Krueger and Casey, 2014).

The key informants from each of the villages were presented with a chart from our study comprising of the clusters and their differentiating characteristics, along with separate cards with names of the farmers from the same village (Kadiyala et al., 2018). The charts were prepared in Hindi, and the basis of creation of the cluster was explained to the eight key informants from each of the villages by the local youth and the researcher. In the first step, the key informants were asked to cross-check whether the cluster created in the study and farmers of the village represented their characteristics or not? If not, they were asked to reshuffle the cards of the individual farmers to other clusters and create a distinct cluster if required.

The results of the categorization of the farmers in the cluster are represented in **Table 5**. It could be observed that for the village Borma, around 97% of the individuals fell into cluster 1 by the characterization performed by the key-informants, 80% of the



**FIGURE 5** | Steps followed in the qualitative analysis for validation and fitting the technology.

**TABLE 5** | Number of individual farmers in each of the clusters identified through the study and cross-checked by the key-informants.

Village	Cluster 1 (Study)	Cluster 1 (Key-informants)	Cluster 2 (Study)	Cluster 2 (Key-informants)	Cluster 3 (Study)	Cluster 3 (Key-informants)	Cluster 4 (Study)	Cluster 4 (Key-informants)
Borma	88	85	19	23	11	10	0	0
Raksi	0	2	10	12	53	61	161	149
Asanbani	0	0	9	8	3	5	40	39

farmers in cluster 2 were the same, approximately 91% of the farmers in cluster 3 while 100% of the farmers in cluster 4 were the same as identified by the study and the key-informants of the village. Concerning the second village Raksi, the first cluster was populated by two farmers by the key informants who did not contain any individual earlier based on our study. The second cluster has seen an addition of two farmers. The third cluster comprised around 85% same farmers, while the fourth cluster consisted of 92% same farmers as identified in our study. The third village, namely, Asanbani, consisted of the same number of farmers in the first cluster followed by 89% same farmers in cluster two. The third cluster saw two farmers' addition while one person was shifted from cluster four to cluster three by the key informants. It is worth noting that the clusters identified in our study were found to be exhaustive by the key informants in all three villages under study. The results confirm earlier findings that reported the existence of a positive relationship between classification of farmers with that of the mathematical classification (Amare et al., 2019; Kuria et al., 2019). Furthermore, support is provided for studies reporting positive relationships between the adoption of agricultural practices and other agricultural innovations through participatory methods (Gyau et al., 2015).

The slight mismatch in the data observed in the table is mainly due to any of the three reasons. The first major reason was attributed to the decrease in income due to the prolonged illness of any member of the family (Mwai and Muriithi, 2016). The second reason was that the main farmer was engaged in some other income source other than farming (Anderzén et al., 2020). The off-source income sources in which the farmers were found engaged were working as insurance agents, owning a local mobile/grocery shop, and engaging in land brokerage. The last reason for such deviation in categorization was because the concerned farming household was prone to alcohol addiction which reduced their capacity to invest or show interest in agriculture (Adu-Baffour et al., 2019). The findings indicate that the participation of the farmers in the focused group discussion was unaffected towards the other groups of the smallholder farms.

### 3.6 Participatory Workshops

Following that, after a 1-week break, participatory workshops were held with the same key informants from each village to learn how technologies were fitted to each of the identified clusters by the key informants themselves (Murgue et al., 2015). The participatory workshops aim to explore integrating local and

**TABLE 6** | Fitting of agricultural technologies to the identified clusters by the key-informants.

Village	Cluster with suitable technology fitted by the key-informants			
	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Borma	Seed production, poultry farming, goat farming, pig farming, integrated farming system, dairy farming, vermicompost production, orchard management (mango, guava), care and management of newly born calves, formulation of balanced cattle feed	Dairy farming, goat farming, poultry and broiler production, pig farming, value additional of milk products, preparation of bakery and confectionery products, production of summer vegetables, seasonal flower cultivation	Mushroom production, summer <i>moong</i> production, seasonal flower production, vegetable production, paddy straw management, nursery raising of agro-forestry trees, beekeeping, preservation of winter fruits and vegetables, insect pest and disease management in trees, clean milk production, techniques to check food adulteration, production technologies of root and leafy vegetable crops, paddy straw management, diagnosis of nutrient deficiency in <i>Rabi</i> crops	Insect pest and disease management in trees, weed management in <i>kharif</i> crops, vegetable and fruits processing, pulp and pickle making, flour mills, fisheries, mushroom production, medicinal plants cultivation, cattle and poultry feed production, rejuvenation of existing orchards, paddy straw management, diagnosis of nutrient deficiency in <i>Rabi</i> crops
Raksi	Dairy farming, vermicompost production, orchard management (mango, guava, coconut), seed production, prevention and control of endo and ecto parasites in dairy animals	Poultry farming, goat farming, pig farming, dairy farming, value additional of milk products, preparation of bakery and confectionery products, poultry and cattle feed production, prevention and control of endo and ecto parasites in dairy animals	Summer vegetables, seasonal flower cultivation, kitchen garden, seasonal flower production, vegetable production, paddy straw management, nursery raising of agro-forestry trees, beekeeping, preservation of winter fruits and vegetables, production technologies of root and leafy vegetable crops, judicious use of irrigation water in <i>Kharif</i> crops	Vegetable and fruits processing, pulp and pickle making, mushroom production, medicinal plants cultivation, cattle and poultry feed production, beekeeping, processing of sugarcane juice, weed management in <i>kharif</i> crops
Asanbani	Mustard processing, dairy farming, vermicompost production, orchard management (mango, guava, coconut), seed production, care and management of newly born calves	Poultry farming, goat farming, pig farming, commercial dairy, value additional of milk products, preparation of bakery and confectionery products, poultry and cattle feed production, medicinal plants cultivation, prevention and control of endo and ecto parasites in dairy animals	Kitchen garden, seasonal flower production, vegetable production, paddy straw management, nursery raising of agro-forestry trees, weed management in <i>kharif</i> crops, beekeeping, preservation of winter fruits and vegetables, oyster mushroom production, clean milk production	Vegetable and fruits processing, pulp and pickle making, flour mills, mushroom production, medicinal plants cultivation, sweet corn production, cattle and poultry feed production, baby corn production, techniques to check food adulteration

scientific knowledge systems (D'aquino et al., 2003). The researcher visited the three villages and the local youth to collect the information that would lead to the fitting of the basket of technologies with each identified cluster.

The step followed in the participatory workshop exercise was that the key informants were shown cards of 30 different agricultural technology which were identified by the Krishi Vigyan Kendra and state extension department. The cards contained the name and brief description of the agricultural technology along with a photograph of the technology. The key informants were asked to distribute the technologies in the identified clusters for the effective targeting of the agricultural technology with the identified farmers of the clusters. The results of the exercise are depicted in **Table 6**.

The fitting of technology in different clusters by the key-informants is based on the characteristics of farmers in the cluster (Scooness et al., 2009; Murgue et al., 2015). The technologies deployed in the three villages demonstrate the technology's applicability for the cluster's farmers and might aid in targeting the intervention to a specific set of farmers. The

fitted agricultural technologies were very much in alliance with the farmer's resource and knowledge base, the options for the marketability of the produce, the skillset and cultural practices prevalent in the villages. The findings are consistent with Shukla et al., 2019 and Lopez-Ridaura et al., 2018, which proposed a typology-based targeted intervention strategy based on a systems approach for livelihood security for regions with scarcity of cultivable land. The farm household income would grow as a result of the initiatives planned for individual villages and districts, according on their resource allocation and market demands.

The findings demonstrate the importance of typology-based study in targeting extension intervention to a specific set of farmers. The study is unique in applying GIS to undertake geospatial analysis of the three villages in demarcating distinct classes that are fallow land, agriculture, forest, buildup area and waterbody for a period of 5 years from the year 2010–2015. The use of geospatial variables along with socioeconomic and biophysical variables led to the capture of heterogeneity in a far more accurate way, which was previously neglected in such

typology-based studies (Ioki et al., 2019; Courault et al., 2020). In addition, the focused group discussions and participatory workshops for the validation of farm types developed from our statistical model provided a basis for the relevance of the farm typologies in the context of smallholder farmers under study.

## 4 CONCLUSION

To date, the studies on farm typologies have tended to ignore the role of subsistence smallholder farmers who are affected by several factors in addition to land and crops under cultivation. In this study, we have provided a statistical methodology for the characterization of farms in developing countries and necessary validation using variables obtained from different domains concerning agricultural practices and GIS to get environmental/geospatial data not available from other datasets. The farm typology classification offers enhanced dominance over the traditional classifications based on the size of the landholding or the characterization based on the agro-ecological characteristics of the farm. The farm types obtained by the typology classification are feasible in the current scenario and are represented by the socioeconomic parameters, bio-physical situation, resource endowment capability and management practices of the farms under study. Also, the identified clusters and underlying typology is based on robust statistical analysis in place of objective classification based on the size and nature of the farm. As such, it is much more acceptable and interpretable to the policymakers and the extension functionaries.

The results' interpretation shows various possibilities that farmers from different clusters could adopt in their farming systems to enhance the income available from the land and increase the sustainability of the farming practices. The considerable impact on the future production systems and food availability would highly depend on the pre-existing livelihood strategies and levels of farm diversification intended by the farm households. The impact of the livestock intensification, as indicated by the positive effect on the income-generating capacity of the farmer, appeared to have a positive effect on all the identified farm types obtained in the study. Based on the different aspects of the four farm typologies observed through our dataset, we conclude that the farmers can diversify their income generation base to other alternative sources of income. For a few to several years, the typologies are prone to change. Hence such studies must be undertaken on a frequent basis to ensure that extension activities are targeted appropriately. The study shows that farm typology may aid agricultural development organisations in simplifying scaling methods and promoting targeted extension approaches to enable the proper solutions for farmers in relevant clusters. The scaling operations organisations might further classify and validate the typologies to make educated judgments on extension decision prioritising and create focused research tools and intervention support systems. The main contribution of this study is that it establishes need for geospatial analysis of the farmland along with socio-economic profiling to explain the typology of farm households based on

matching of agricultural technology. In addition, extension intervention could be implemented on the district level by identifying different components affecting the farming systems including cropping, livestock and allied production interventions. The targeting of extension intervention through this typology study offers the policymakers a mix of options to reach smallholders based on their potential and interests rather than prescribing a "one-size-fits-all" strategy.

The major limitation of the study was the time and fund constraint, which allowed the researchers to zoom in on limited geographies of three villages in three different districts of Jharkhand, India. Future research in the domain should also consider intra-household interactions and dynamics to formulate innovation pathways appropriate for each level of endowment and livelihood strategies captured in the typology. The researchers should also identify farm typologies of smallholder farmers in developing countries with small landholding sizes and streamline the extension interventions based on the identified systems in active collaboration with the extension agencies and allied institutions. We conclude by reflecting on how these typologies and the heterogeneity explained by the farming systems may be effectively used by the extension agencies in designing appropriate policy interventions to support smallholders imbibing technological innovations in agriculture.

## DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

## ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Advisory committee for doctoral study at Bidhan Chandra Krishi Viswavidyalaya, India. The patients/participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

## AUTHOR CONTRIBUTIONS

Conceptualization: DB and AS. Formal analysis: PP and AS. Methodology: AS, DB, and AG. Resources: DB, RKS.

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