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FARM HOUSEHOLDS' TYPOLOGY: IMPLICATIONS FOR TECHNOLOGICAL INTERVENTIONS IN THE RICE ENVIRONMENT IN FOGERA PLAIN, ETHIOPIA

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ABSTRACT

The rice-based agricultural system in the Fogera Plain exhibits considerable heterogeneity across its ecosystem. This study aims to develop a farm typology that categorizes rice farms into distinct groups to facilitate targeted technological interventions. Using multivariate data mining techniques-Principal Component Analysis (PCA) and Cluster Analysis (CA)-data were collected from 230 farm households based on biophysical and socioeconomic characteristics. PCA identified five principal components explaining 62.7% of the total variance, with the first two components accounting for 44%. Cluster analysis delineated five farm types: Input-based Rainfed (FTP1), Off-farm Income-dependent (FTP2), Irrigation-based (FTP3), Livestock-based (FTP4), and Small and Marginal Rainfed-Based (FTP5). Notably, FTP3 and FTP4 utilized the highest proportions of irrigation water (26% and 21%), while FTP5 and FTP2 had the lowest water use (14% and 11%). The findings give emphasis to the need for developing small-scale irrigation infrastructure, especially for FTP5 and FTP2, to mitigate water shortages and enhance rice productivity. Therefore, the use of the identified farm-type-specific character may facilitate the adoption of farm-type-specific technologies and aid in the creation of an environment that is suitable for policy insights and extension services, thereby enabling more efficient and sustainable.

Keywords: Farm typology, Multivariate analysis, Rice ecosystem, Irrigation, Ethiopia

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1. INTRODUCTION

A rapidly growing global population need food, clothing, and energy from agricultural farming while limiting negative effects on the environment and other factors (Roy et al. 2006). The diversity of farming systems, shaped by biophysical and socioeconomic factors, presents both challenges and opportunities for development (Dixon et al. 2001; Giller et al. 2006). Understanding system complexity and conditions is crucial for customizing management and effectively scaling interventions (Giller 2013; Girma 2022). Farm typologies also enable better resource allocation, supporting inclusive, sustainable development, food security, and poverty reduction goals (Hammond et al. 2017; Ayele et al. 2021).

The heterogeneity of farming systems—driven by biophysical and socioeconomic diversity—poses challenges and opportunities for development interventions (Dixon et al. 2001; Giller et al. 2006). Understanding farm diversity through typologies enables tailored policies and technologies that align with farmers' resource endowments and livelihood strategies (Tittonell et al. 2010; Sarker et al. 2021; Ayele et al. 2021). Numerous studies have described East African smallholder farming systems, identifying the distinct heterogeneity of farming households, their vast range of variation, and the complexity of smallholder farms (Tittonell et al. 2010; Hassall et al. 2023).

According to Sakané et al. (2013), the characterization of farm typology aids in the understanding of cross-scale interactions among the primary drivers and determinants of farm diversity as well as the grouping of the diversity of farm types. Through simplification and division of farms into distinct farm types, farm typologies and characterization of farming systems have been widely employed to understand systems complexity, heterogeneity, and agricultural development trajectories (Alvarez et al. 2018; Girma 2022). Farm typologies are applied in agriculture and rural development to realise the diversity of farming systems and farmers within a specific area

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(Alvarez et al. 2018; Kumar et al. 2019; Awoke Eshetae et al. 2024). According to Kuivanen et al. (2016) and Tittonell et al. (2020), farm typology aids in the grouping of diverse farm types with shared characters, hence facilitating the adoption of a more tailored strategy for agricultural development. Using a variety of criteria that frequently overlap across regions and agroecological zones, several studies have identified farmer classes and livelihood patterns to describe farming systems in various parts of Africa (Chikowo et al. 2014).

Some publications (Pacini et al. 2014; Kuivanen et al. 2016) proposed using multivariate data mining techniques (PCA and CA) for farm typology analysis to group farm policies, markets, and farm household integration in value chains are examples of institutional, socioeconomic, and biophysical elements that contribute to farm type differentiation (Alvarez et al. 2018). Typology is defined groups of farms or farmers with minimum variation within, and maximum variation to other groups (Marshall et al. 2021). According to Sarker et al. 2021), grouping farmers according to their socioeconomic, agronomic, and demographic traits, farming methods, and the resources at their disposal is useful for creating extension services, credit facilities, and technology innovation and adoption plans that are tailored to the needs of each farmer's group. Farm typologies are used to study the appropriate fertilizer application (Tittonell et al. 2006), adoption of climate-smart agriculture practices (Makate et al. 2018), water use efficiency (Senthilkumar et al. 2009), food security (Lopez-Ridaura et al. 2018) and mixed crop-livestock farming system (Awoke Eshetae et al. 2024). A farm's type can be described using information from local stakeholders' criteria or by analyzing data from farm households, which offers a wealth of quantitative and qualitative variables (Kuivanen et al. 2016).

Based on expert knowledge and the application of multivariate statistical techniques such as Principal Component Analysis (PCA) and Cluster Analysis (CA), farm typology in southern Ethiopia has been characterized into four main types: (1) crop-oriented farms, (2) livestock-oriented farms, (3) mixed crop-livestock farms, and (4) small farms (Berre et al. 2019). Similarly, Kebede et al. (2019) classified farmers into four primary farm types based on various parameters including farm size, number of animals, crop diversity, household capacity to send children to school, and housing type. Regarding irrigation schemes in Ethiopia, Agide et al. (2016) identified typologies based on water source, abstraction and conveyance systems, flow control structures, water management practices, and the organization of water users, categorizing schemes into modern, semi-modern, and traditional types to inform policy development.

In the context of the rice ecosystem on the Fogera Plain, there exists considerable variation among farm types. However, limited information is available on the livelihood strategies, farm diversity patterns, and how households utilize this diversity to inform targeted policy support and technological interventions across the rice ecosystem. Given the critical importance of rice for local livelihoods and national food security, understanding farm typologies in Fogera is vital for developing context-specific technological solutions and a supportive policy environment. Thus, the objective of this research was to create a typology of rice farms into distinct farm groups to facilitate targeted technological interventions in the Fogera Plain, Ethiopia.

2. MATERIALS AND METHODS

2.1. Description of the Study Area

The research was conducted in Fogera and Libo Kemkem districts of Ethiopia’s Amhara Regional State, situated near Lake Tana. The latitudinal and longitudinal ranges that contain it are 11°40′N to 12°20′N and 37°30′E to 38°00′E, respectively (Fig. 1). The climate features an average annual temperature of 20.63°C (range 12.8–28.08°C) and annual rainfall averaging 1323 mm, supporting rice cultivation in lowland and upland ecosystems (Fig. 1).

2.2. Sampling Techniques and Sample Size

A three-stage stratified random sampling approach was employed. First, two districts were randomly selected from six rice-growing districts. Second, lowland and upland rice ecosystems within each district were identified. Third, peasant associations (PAs) were randomly chosen (Table 1). The questionnaire experienced pre-testing with farm households to enhance its relevance. Each study block (upland and lowland ecosystem) encompassed three focus groups. Eight households from each focus group engaged in discussions. Six focus group discussions included rice-growing households. In total, 48 households participated in the FGD sessions across research districts. Additionally, for each district in Table 1, five development agents, one extension officer, one value chain expert, and two district experts were consulted as key informants. The study incorporated focus groups and key informant interviews as complementary methods to validate household survey data across the rice ecosystem.

Data completeness and quality were precisely examined. To eliminate outliers and enhance the quality, boxplots were employed to identify outliers. As a result, 230 questionnaires were considered to have complete responses and to have valid data, which is why 10 questionnaires were eliminated from the study in Table 1. Following the usage of the sampled farms as replications to identify the major farm types, ten farms per farm type

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were randomly chosen and subsequently questioned to provide a comprehensive characterization of farm household water use during crop growing seasons, as shown in Table 4.

Table 1: Sampled respondents by the PAs per households

PAs per District	Rice ecosystem	PAs	HHs per block	FGD per block	Eight HHs per FGD
Fogera (37PAs)	Upland (9PAs)	3	45	1	8
	Low land (19PAs)	5	75	2	16
Libo Kemkim (31PAs)	Upland (12PAs)	5	75	2	16
	Low land (6PAs)	3	35	1	8
Total		16	230	6	48

Notes: PAs, peasant associations; HHs, households; FGD, focus group discussion, block (rice ecosystem)

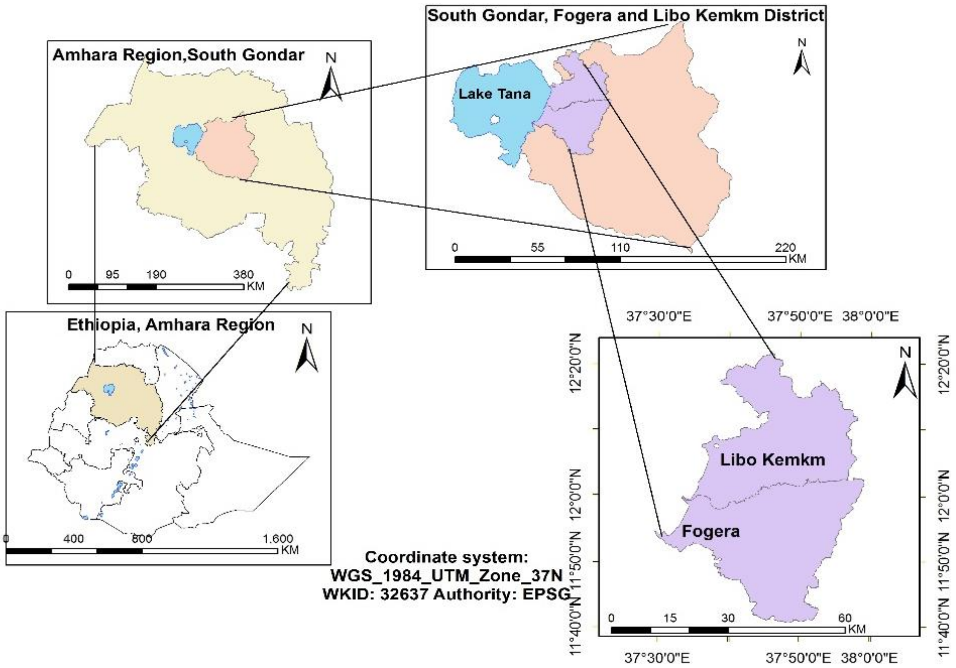

Fig. 1: Location map of the study area (Fogera and Libo Kemkm Districts).

2.3. Data Collection

A field survey, consisting of questionnaires for households (HHs), checklists for FGD, guiding questions for key informant discussions, and field observations, was carried out among farm HHs over two months (January–February 2019. Biophysical and socioeconomic farm variables were used to gather the data, such as age, family labor, farm household education, farm size, credit availability, input uses, off-farm activities, wealth rank, farming experience, number of crops produced annually, number of animal units, availability of fishing, power services, irrigation use and facilities, including off-farm income and water use from various sources throughout the farm type.

2.4. Method of Data Analysis

Principal component analysis (PCA) was employed to assess variation patterns and the importance of variables in elucidating observed diversity. The Kaiser–Myer–Olkin (KMO) index and Bartlett's sphericity test were applied to analyze 24 factors from datasets encompassing 230 farm households (Field et al. 2012). The current study on rice farm typology development employed PCA, CA, and expert validation as outlined by Alvarez et al. (2018), Kuivanen et al. (2016) and Hassall et al. (2023). Integrating different methodological approaches could help to leverage the benefits of different knowledge systems for developing farm typologies outlined by Berre et al. (2019) and Assogba et al. (2022). According to Kaiser's criterion (Foguesatto et al. 2020), the first five principal components with eigenvalues greater than or equal to one were selected. Biplot analysis was conducted to explore multivariate patterns regarding variance, correlations, inter-unit distances, and their proximities to the origin (Kohler and Luniak 2005). PCA is widely recognized for determining cluster numbers, as evidenced by Penkova (2017) and Ding and He (2004). The classification of farms was validated through field observations, local insights, and consensus from agricultural experts and practitioners regarding the diversity of local farming systems, as noted by Pacini et al. (2014). Data analysis was performed utilizing R software and SPSS Version 22.

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3. RESULTS & DISCUSSION

3.1. Principal Component Analysis

The findings revealed that the communality value was 0.30 the KMO indices were 0.7, and the Bartlett sphericity test was very significant (p<0.001), all of which are considered acceptable (Field et al. 2012). Five main components with Eigenvalues greater than one were found by PCA; one was kept for additional examination in Table 2. Table 2 also provides the rotated factor (Varimax) matrix of independent variables with unequal factor loadings. Table 2's communality column displays the total variance of each variable that was kept in the components.

Table 2: Five PCA components derived by PCA with loadings for farm variables and % cumulative variance explained

Variables	PC1	PC2	PC3	PC4	PC5	Communality
Household size	0.218	-0.123	0.876	0.134	-0.03	0.849
Farm size	0.614	-0.032	0.212	0.667	-0.114	0.88
Number of oxen	0.677	0.099	0.163	0.187	-0.19	0.566
Farm experience	0.145	-0.094	0.706	0.086	-0.113	0.549
Number of animal fatting	0.095	0.455	-0.16	-0.085	0.625	0.639
The education level of the HH head	0.431	0.533	-0.249	0.1	0.28	0.62
Credit access	0.325	0.554	-0.039	-0.003	0.276	0.49
Extension service	0.227	0.752	-0.17	-0.136	0.238	0.721
Off-farm activities	-0.395	0.016	0.028	0.006	0.761	0.736
Number of sheep	-0.111	0.876	0.042	0.082	-0.133	0.806
Number of chicken	-0.174	0.851	-0.056	-0.065	-0.028	0.762
Number of cropping per year	0.615	0.132	0.208	0.2	-0.174	0.508
The average educational level of household	0.633	0.067	0.163	-0.145	0.307	0.548
Number of full-time laborers size	0.045	-0.099	0.701	0.159	0.017	0.528
Number of part-time laborers size	0.31	-0.009	0.746	0.002	0.019	0.654
Dairy size	0.435	0.119	0.379	0.025	0.001	0.348
Hive size	0.684	0.034	0.024	0.076	-0.087	0.482
Input access	0.715	-0.007	0.144	0.104	-0.03	0.543
Wealth rank	0.726	0.033	0.167	0.326	-0.035	0.663
Power supply services	0.7	-0.018	0.095	0.111	0.103	0.522
Irrigated farm size/ha	0.329	-0.006	0.079	0.857	-0.061	0.852
Rainfed farm size/ha	0.692	-0.053	0.268	0.358	-0.124	0.698
Irrigation equipment	0.357	-0.056	0.117	0.761	0.015	0.724
Fish availability	-0.035	-0.004	0.071	0.584	0.003	0.348
Eigenvalue	7.013	3.585	1.817	1.483	1.139	
% of Variance	29.222	14.937	7.570	6.179	4.746	
Cumulative explained variance%	29.222	44.160	51.730	57.908	62.655	

The variables that had the highest influence were determined to be the first principal component (PC1) variables. It contributed 29% to the overall variance, while the second main component (PC2) contributed 15%. Of the overall variation, 44% was explained by PCs 1 and 2. The input access, farm size, HHs' average educational rank, wealth rank, power service, rainfed farming, number of oxen, number of croppings yearly, number of dairy animals, and number of hives per household (HH) are the characteristics that define the PC1. The number of chickens and sheep, the credit and extension services, the educational rank of the HH head, and animal fatting were other characteristics that were taken into account while determining the PC2. Although they had comparatively low power service, three more main components also meaningfully explained variation. Together, these three factors (PC3, PC4, and PC5) accounted for 18.5% of the variance in the whole. The variables characterizing the size of the household, the number of family members working full-time, the number of family members working part-time, and farming experience were all strongly correlated with the third main component (PC3). A high correlation was observed between the fourth main component (PC4) and factors about irrigation water access, farm size, irrigation equipment, and fishing activities. In this sense, off-farm activities, animal fattening, and the average household educational rank are also defined as the fifth main component (PC5). When combined, the five main components in Table 2 accounted for 62.70% of the variability. According to Goswami et al. (2014), the farm types that have been identified are manageable in terms of quantity and reflect the farms' socioeconomic and resource ownership and management perspective. Senthilkumar et al. (2009) found that socioeconomic and biophysical parameters are used to classify different types of farms. The higher loading in Table 2 indicates that certain variables like farm size, oxen count, number of crops planted year^{-1}, rainfed farming, power service, input accessibility, and wealth rank—contribute more to the principal components than other variables in PC1 in Table 2. The loading plot in Fig. 2's

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multivariate pattern of the variables showed that the variables near the origin (x, y), for example, off-farm activities and fishing had smaller loading and a low contribution to farm type grouping. Farm size, irrigation access, credit availability, education level, input availability, number of crops planted annually, rainfed farming exclusively, irrigation equipment, and ox count were among the variables located far from the origin that had the highest loading and the highest contribution to the farm type grouping in Fig. 2. Variables from the rotational factor matrix with high factor loadings and high communality were taken into consideration for the PC interpretation (Manly and Manly 1994). According to Kohler and Luniak (2005), biplot analysis aids in examining the multivariate pattern of the variables in the data matrix by revealing the variance, correlations, and distances between units as well as their distant locations from the variables' origins. The PCA coefficients, or "loadings," are represented by these relative positions of the variable lines.

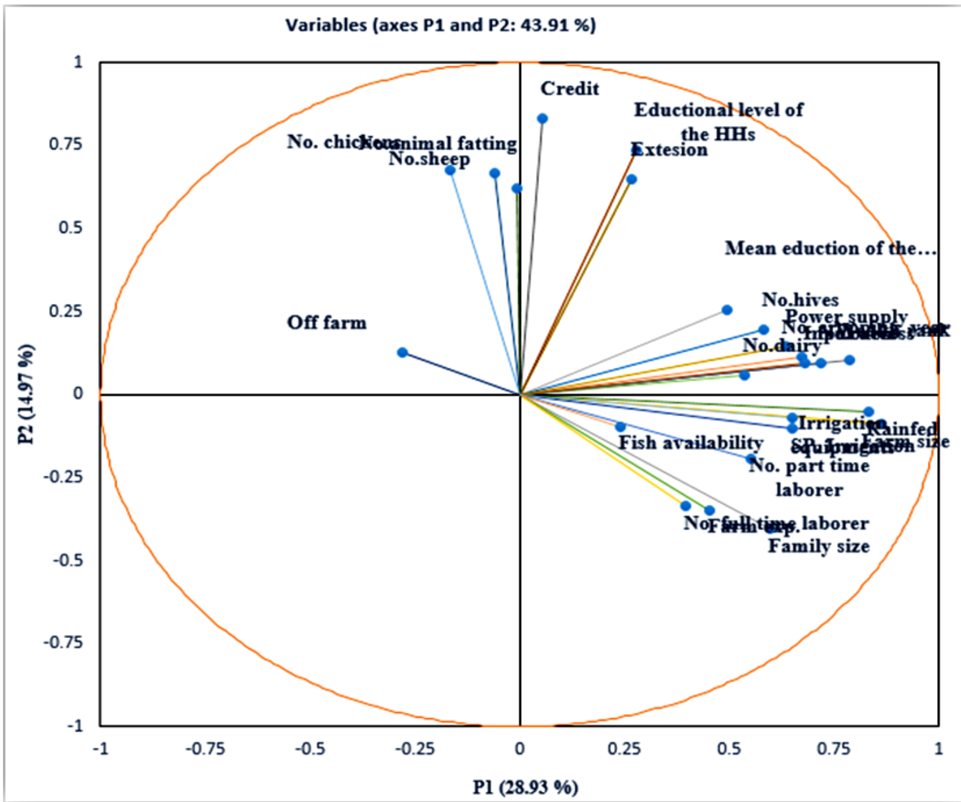

Fig. 2: Loading plot showing the association and contribution farm variables (%).

Descriptive variables are grouped as follows: household size (hhsize), number part-time laborers size (ptlsize), farm experience (frmexp), number of full-time laborers size (ftlsize), farm size (frmsize), rainfed farm size/ha (rainfrmsize), number of oxen (oxnsize), number of cropping per year (ncrop), hive size (hivsize), input access (inptaccess), wealth rank (wlrnk), power supply services (psservice), the average educational level of household (aeduhh), dairy size (dirsize), irrigated farm size/ha (irrgfrmsize), irrigation equipment (irrgequipment), fish availability (access), animal fatting size (anmfsize), extension service (extservice), education level of the hh head (eduhh), credit access (crdtaccess), number of chicken (chknsize), number of sheep (shpsize), off-farm activities (offfarm).

3.2. Cluster Analysis

The number of principal components dictated the number of clusters, which were sampled from various farm households throughout the rice ecosystem. As a useful farm type grouping, the farm households were clustered by cluster algorithm and cross-checked using field observation and the agreement of various household groups, development agents, value chain experts, and agricultural experts (validation panel). Alvarez et al. (2018) suggested that the typology development should be guided by local agriculture structures, drivers, and local stakeholders' participation (Pacini et al. 2014). The optimal number of clusters obtained through the agglomerative hierarchical clustering approach was also evaluated using the Elbow method (Syakur et al. 2018; Shi et al. 2021) and the Silhouette method (Wang et al. 2016), which are commonly employed in K-means clustering. The present work employed PCA, K-means clustering, and dendrogram tree approaches to distinguish five distinct farm types, each possessing unique properties. In Table 3, they have a distinct set of attributes and properties. Table 3 displays the estimated mean values of each driving variable for each type of farm. Table 3 and 4 illustrate how the five different farm types in Fogera Plain differed substantially in terms of driving factors and water usage methods. Types of farms: input-based rainfed (FTP1), off-farm-income-based (FTP2), irrigation-based (FYP3), livestock-based (FTP4), and Small and Marginal Rainfed -Based (FTP5). Each farm type has unique characteristics. Table 3 illustrates these classifications. The degree of autonomy for each type of farm was defined with the use of this grouping method. In this regard, four main farm types were found by Berre et al. (2019) through their study of farm typology delineation in southern Ethiopia: (1) crop-oriented farms, (2) livestock-oriented farms, (3) mixed crop-livestock farms, and (4) small farms. According to Chatterjee et al. (2015), there are four different types of rice-based integrated farming in India: farms that grow food grains and jute; farms that have livestock and fisheries and generate a lot of revenue off-farm; farms that are crop-based and generate income off-farm; and farms that cultivate fruits and vegetables.

Table 3: Characteristics of farm types, identified by cluster analysis

Variable	FTP1	FTP2	FTP3	FTP4	FTP5
Household size (hhsize)	5.49	4.19	6.27	4.80	4.31
Farm size (frmsize)	1.63	0.89	1.90	1.64	1.14
Number of oxen (oxnsize)	2.20	1.40	2.45	2.28	1.52
Farm experience (frmexp)	3.05	2.58	3.13	2.96	2.69
Number of animal fatting (anmfsize)	0.82	1.35	0.20	1.64	0.48
Education level of the hh head (eduhh)	1.33	1.31	1.13	1.80	1.08
Credit access (crdtaccess)	1.78	1.88	1.67	2.22	1.39
Extension service (extservice)	1.58	2.25	1.40	2.50	1.27
Off-farm activities (offfarm)	1.45	2.00	1.33	1.36	1.53
Number of sheep (shpsize)	0.00	5.44	3.67	7.56	0.02
Number of chicken (chknsize)	1.31	7.67	.33	7.56	0.79
Number of cropping per year (ncrop)	1.89	1.52	1.93	1.90	1.55
The average education of household (aeduhh)	6.05	1.42	1.96	5.03	1.27
Number of full-time laborer (ftlsize)	2.60	2.33	3.40	2.40	2.34
Number part-time laborer (ptlsize)	1.87	.85	1.80	1.70	1.00
Dairy SIZE (dirsize)	2.16	1.50	2.13	2.14	1.16
Hive size (hivsize)	0.91	0.27	0.60	0.94	0.34
Input access (inptaccess)	2.55	1.69	2.60	2.34	1.73
Wealth rank (wlrnk)	2.22	1.48	2.53	2.16	1.50
Power supply services (psservice)	2.55	1.54	1.80	2.30	1.71
Irrigated farm size/ha (irrgfrmsize)	0.29	0.10	0.50	0.35	0.17
Rainfed farm size/ha (rainfrmsize)	1.34	0.79	1.40	1.29	0.97
Irrigation equipment (irrgequipment)	1.80	1.27	2.00	1.90	1.40
Fish availability (fshaccess)	1.85	1.58	2.20	1.92	1.68

descriptive variables are grouped as follows: for wlrnk , 3=wealthy; 2=medium; 1=poor. for eduhh, 4 =13years+; 3= 9-12th years; 2=5-8 years; 1=0–4 years. for crdtaccess, 4=high; 3=medium; 2= low; 1= none. for extservice , 4=3 times contact and above per month; 3=2 times contact per month; 2=1 time contact per month; 1=none. for inptaccess , 4=seed, fertilizers, and pesticides; 3= seed and fertilizers; 2=seed or fertilizers; 1= none. for psservice, 3= electric/ solar services; 2=energy saving technology; 1=none. for frmexp , 4= >25 years (very high); 3= 15-25 (high); 2=10-15 (medium); 1= <10 years (low). for offfarm , 4= major income sources; 3=partial income sources; 2=rarely income sources, 1=none. for fshaccess, 4= lake; 3= natural seasonal ponds; 2= river; 1=none, for irrgequpment, 3= water pump;2= pedal pump/gravity acess;1=none

Table 4: Water use practices per farm type

Water sources	FTP1	FTP2	FTP3	FTP4	FTP5
River water sources (ha)+rainfed	0.214	0.097	0.27	0.292	0.12
Groundwater sources (well) (ha)+rainfed	0.076	0.003	0.22	0.067	0.05
Rainfed water alone (ha)	1.34	0.79	1.40	1.29	0.97
Farm size (Irrigated+ Rainfed) (ha)	1.63	0.89	1.89	1.64	1.14
Rainfed alone farming %	82.00	89.00	74.00	79.00	86
Irrigated+rainfed farming %	18.00	11	26.00	21.00	14

3.3. Farm Type Characterization

3.3.1. Input-based Rainfed (FTP1): Households in the FTP1 group are categorized as medium wealth within wealth class 2. They allocate a limited area to maize and finger millet cultivation each year and grow rice-based legumes (such as grass peas, lentils, oats, and chickpeas after rice) on an average of 1.63 hectares. 81% of family members are engaged in either full-time or part-time employment, with an average household size of 5.5 individuals. Due to

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educational and other obligations, 34% of family members work part-time on the farm, while nearly half (47%) work full-time. These farms typically have a small number of livestock, such as chickens and sheep, but more than two draft animals are present, indicating a shift towards an input-dependent rainfed production approach outlined in Table 3. Only 18% of farm areas benefit from flood irrigation, utilized primarily for supplementary rice irrigation and small vegetable plots (refer to Table 3). Access to irrigation water on these farms is relatively limited. Farm type 1 is marked by an array of higher-loading variables, including the average education level of the household, increased input usage, non-improved dairy cows, access to credit, number of beehives, power services, farm size, quantity of draft animals, wealth ranking, and rainfed farming as demonstrated in Table 3. Thus, the loading plot in Fig. 3 reflects a strong correlation among these factors, closely associated with the FTP1 along the biplot axis. Although farmers are utilizing more inputs, which requires higher use of pesticides, fertilizers, and herbicides—potentially posing significant environmental risks within the rice production system in the Fogera Plain—there is a pressing need for extension support, environmental monitoring, and guidance on low-input technologies to sustain rice production in aquatic environments. Goswami et al. (2014) noted similar results in an Indian study, identifying input-intensive farms by large land sizes, extensive family composition, generally elevated family education levels, increased input usage, and a notably higher diversity of crops. Such input-heavy farms, characterized by considerable capital and management demands, can create unsustainable farming conditions. Intensive farming offers a promising strategy to address production gaps but heavily depends on resource inputs lake water, chemicals, and energy. This reliance raises significant environmental risk, including pollution of water, land, and air and poses threats to human health and ecosystem (Gaffney et al. 2019).

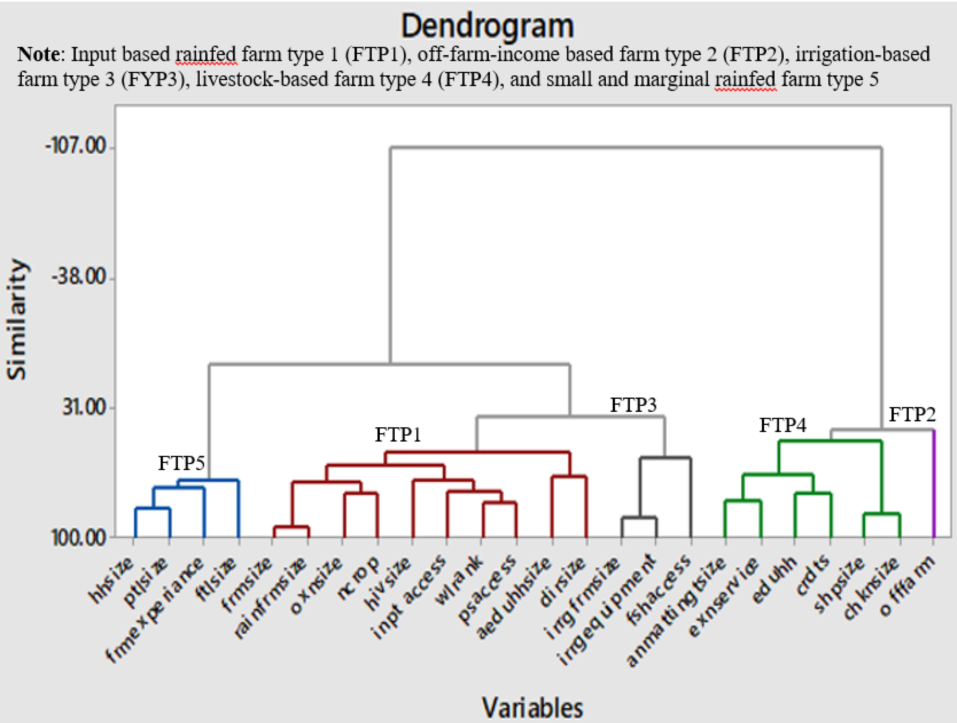

Fig. 3: Dendrogram tree showing the relationship between farm types and variables.

3.3.2. Off-farm Income-based (FTP2): Households categorized as disadvantaged (wealth class 1) operate small-scale farms averaging less than 0.89 hectares and predominantly depend on off-farm income sources. These households typically have a small household size, averaging 4.19 members. Their agricultural activities mainly involve cultivating rice, maize, and finger millet on limited landholdings, and they prioritize off-farm pursuits over on-farm activities. Only about 20% of family members participate part-time in farming, whereas nearly 56% are engaged full-time in off-farm work. This household type is characterized by higher engagement in off-farm activities, small-scale farming operations, smaller family units, and modest livestock holdings, including sheep, poultry, and chicken fattening. They utilize limited traditional farming tools but benefit from strong extension services and access to credit. The FTP2 loading plot indicates a significant association with off-farm activities, as shown in Fig. 3. Due to lack of irrigation infrastructure, many of these farmers face water scarcity during the later stages of the cropping season. Their primary aim in crop cultivation is to meet family food needs; additionally, they work as agricultural laborers on other farms, seek employment in urban areas, participate in local projects, or

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operate small artisanal businesses such as brewing beer. Rural households diversify their livelihoods through a combination of farm, non-farm, and off-farm activities, with non-farm income playing a crucial role (Agbarevo & Nmeregini 2019). Non-farm activities encompass processing, trading, manufacturing, and local services, excluding direct agricultural and fishing pursuits (Kazungu & Guuroh, 2014). Small farms with limited livestock depend more heavily on off-farm work, which often involves seasonal migration and low levels of investment (Goswami et al. 2014; Berre et al. 2016). In Ghana, subsistence farms are notably small, with limited labor resources and income derived from poultry and other off-farm activities (Kuivanen et al. 2016).The findings indicate that the off-farm income-based farm type in Fogera Plain represents a highly vulnerable subset of the rice farm typology, underscoring the necessity for targeted intervention efforts towards this group.

3.3.3. Irrigation-based (FTP3): When compared to other farm types, the irrigation-based farm type has the following characteristics: fishing, a large farm size, high wealth rank, better education level, more cropping per year, and the highest family member in Table 3. It also has relatively high access to irrigation water and facilities. According to Table 3, FTP3 (Wealth Class 3) was the wealthiest in comparison. Their farm spanned an average of 1.9 hectares. The average household size was 6.27 people, which is relatively substantial. On average grew one rice and second legume and vegetables-based crops per year. Because this style of farm had better access to irrigation, it could also produce more vegetables for both local and distant markets. The majority of the family members in farm households worked mostly as farmers. Merely 54% of the household members worked full-time on their farms, while 29% worked part-time due to part-time study, social work, and other activities. Only 83% of their total labor was committed to farming. The family in Table 3 primarily employed the farm type, which owned two or more dairy animals, for fishing and milk production. Table 3 shows that, overall, 26% of their farm size had access to flood irrigation. Similarly, Fig. 3's loading plot, which also displayed similar characteristics, strongly correlated with FTP3 along the biplot axis. This analysis indicates farm households with better access to irrigation water and facilities in combination with rain-fed farming have better crop diversification and significant differences in net return as compared to those farm households relying on rainfed farming. According to this data, farm households that combine rain-fed farming with flood irrigation have more diverse crops and substantial resource profile when compared to those farm households relying on rainfed farming. According to Robert et al. (2017), Table 3 and 4 demonstrate the characteristics of large, diverse, productive farms: higher input costs, more irrigation capacity, larger land holdings, and improved electrical services.

3.3.4. Livestock-based (FTP4): Farms with a livestock focus fall under the wealthy class 3 (i.e. wealthy). The average family size was 4.8 members, which is considered medium. They had 1.64 ha and cultivated crops only on average and grew one rice and second crop legumes and vegetables-based crops per year during the main rainy season with some farm households irrigating crops in the later growth stages. Some farm households also used water from rivers or groundwater sources to irrigate their crops during the terminal stages of growth. Although farming was their main source of revenue, Table 3 shows that they hardly ever engage in off-farm activities. The family members and homes on farms were well-educated. A family of four members made up the average, and fifty percent of them worked on the farm full-time, while thirty-five percent did so part-time. Table 3 shows that, overall, 21% of their farm size had access to flood irrigation. FTP4 farm households were distinguished by a comparatively higher family educational level, access to credit and extension services, a greater number of sheep and chickens, more animal fatting, and dairy farm characteristics. Table 3 shows that the farms in this category had more animals per livestock unit. Similarly, Fig. 3's loading plot demonstrates that the variables exhibited a strong biplot axis association with FTP4. According to Ellis-Jones et al. (2012), people keep cattle, sheep, goats, and chickens for food, money, and wealth accumulation. They also keep them somewhat for their ability to provide inputs like manure (used as organic fertilizer) and draft power. The medium resource-endowed livestock-based farming method, as stated by Kuivanen et al. (2016), is focused on saving through livestock (using resources earned from crop sales and/or animal husbandry) and increasing crop and livestock productivity and diversification (Mekuria & Mekonnen 2018). Moreover, most households use crops and livestock for risk reduction and coping strategies (Kassie et al. 2017).

3.3.5. Small and Marginal Rainfed -Based-based (FTP5): Type 5 farms were quite poor and belonged to Class 1 wealth. Their farm was of a moderate size, averaging 1.14 hectares. The average HH size was 4.31 people, which is considered medium. The members of the farm HH members had lesser wealth and educational levels. For the majority of these farm HHs, rainfed farming served as their main source of income, with some also relying on activities conducted off the farm. There were extremely few dairy animals and small ruminants (sheep and chicken) on this type of farm. They lacked access to energy-saving resources, very little irrigation, and very little input. 77% of their labor was used for farming; just 54% worked on their farms full-time, and 23% worked part-time because of other or off-farm activities. In all, rainfed sources provided 85% of the water used for crop cultivation; nevertheless, Table 3 shows extremely small farm families irrigating crops during later growth phases. Table 3 illustrates how the size of the HH, the number of family laborers employed full-time and part-time on the farm, and the farming experience farm factors all reflected FTP5. Similar to this, Fig. 3's loading plot of these variables around FTP5 along the biplot axis showed a strong relationship and proximity. Similar findings were reported by Robert et al. (2017). The Small and Marginal Rainfed -Based farm is defined by low input, more rainfed, fewer land holdings, and limited irrigation access. Due to resource constraints, farms with limited resources are in danger (Kuivanen et al. 2016). In the Fogera Plain, Small and Marginal Rainfed-Based farming is largely dependent on rainfall to grow crops, which exposes them to water scarcity in the latter part of the cropping season.

3.4. Water use Practices per Farm Type

The rice ecosystem's water sources support crop production for farm households. In FTP1, 18% of irrigation comes from rivers and wells, while 82% is rainfed. Table 4 indicates that only terminal rice growth stages and a small area for vegetables utilize all irrigation sources. FTP2 relies predominantly on rainfed agriculture. Rainfed farming constitutes 89% of crops, with 11% supplemented by rivers and wells during rice's terminal growth stages. Table 4 reveals that dependence on rainfed water constrains agricultural options for rice and cereals. Due to insufficient rainfall, only limited crops like finger millet and small-scale maize and rice are cultivated for domestic consumption. Vegetables are unsuitable for consistent cultivation due to their sensitivity to water stress. Moisture stress, which is especially prevalent late in the season due to an early cessation of rainfall, frequently affects the rain-fed lowland rice production in the Fogera Plain (Tilahun et al. 2013). Inadequate rainfall during the reproductive growth stages limits rice production across the rice ecosystem in the rainfed lowland rice (Molla et al. 2021; Barati et al. 2022). Farm households in FTP3 had access to 26% of the water needed for irrigation from wells and rivers, and the contribution of flood irrigation was relatively high compared with other farm types. They use flood irrigation to produce vegetables more effectively, and they also encourage rainfed farming for rice, oats, and lentils during their later growth stages. Additionally, 21% of FTP4 utilizes flood irrigation, although 79% remains rainfed. Households employ flood irrigation for various crops, including rice, lentils, oats, and forage, alongside a small area for vegetables. In contrast to farm types 1, 3, and 4, farm type 5 relies 86% on rainfed water for crop production. Only 14% of water usage in Table 4 is attributed to other households, who depend on wells and rivers for rainfed rice and minimal vegetable cultivation, constrained by limited water access. FTP3 (26%) and FTP4 (21%) demonstrate the highest water utilization per season among sources. Conversely, FTP5 and FTP2 use less at 14% and 11% annually, respectively. In the Fogera Plain, irrigation from wells and rivers supports stable rainfed rice production. To enhance productivity and sustain rice production in Fogera, addressing irrigation water deficits through appropriate small-scale infrastructure for FTP5 and FTP2 is essential.

4. CONCLUSION

This study identified five distinct rice farm types in Fogera Plain based on socioeconomic and biophysical factors. The cluster topology farm types were: input-based rainfed (FTP1), off-farm income-based (FTP2), irrigation-based (FTP3), livestock-based (FTP4), and Small and Marginal Rainfed-Based (FTP5). The farm types differed notably in water use practices and resource profiles, with FTP3 and FTP4 showing higher irrigation reliance while, FTP5 and FTP2 used less. Addressing water access limitations for FTP5 and FTP2 through targeted infrastructure development is crucial for sustainable rice production. The farm typology provides a foundation for designing farm-specific technological solutions and informing policy decisions to foster resilient and efficient rice farming systems, with implications for targeted interventions such as sustainable input management and irrigation upgrades for FTP1 and FTP3, water harvesting and small-scale irrigation infrastructure for FTP2 and FTP5, and livestock technologies for FTP4. It is concluded that the types of rice farms that have been identified will help focus on the particular needs and priorities that should be addressed through the right technology services, policy interventions, and management decisions. This will increase the productivity and ecosystem-wide benefits of farm-type-specific technologies.

Further Research Directions: There is still room for more investigation and inquiry, even if this study offers insightful information about the diversity of farm systems in the Fogera Plain. Future studies could focus on over time and evaluate the usefulness of technology and policy intervention programs. Furthermore, more comprehensive knowledge of the biophysical and socioeconomic driving factors impacting technology adoption may be possible through comparison studies conducted across various rice ecosystem settings in Ethiopia and other comparable regions.

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Data Availability: The data that support the findings of this study are available from the corresponding author upon request.

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