Heliyon 9 (2023) e20526

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

A scalable approach to improve CSA targeting practices among smallholder farmers

Cyrus Muriithi [*,1], Caroline Mwongera [1], Wuletawu Abera, Christine G.K. Chege, Issa Ouedraogo

The Alliance of Bioversity International and International Center for Tropical Agriculture (CIAT), Duduville Campus Off Kasarani Road P.O. Box 823-00621, Nairobi, Kenya

ARTICLE INFO

Keywords:
Social economic and biophysical factors
Livelihood capitals
Factor analysis for mixed data
Typology
Targeting
Scaling

ABSTRACT

With climate change, population growth, and land degradation exerting mounting pressures on agricultural systems in developing countries, climate-smart agriculture (CSA) strategies have been prioritized as a means to strengthen smallholder farmers' resilience. However, precise targeting methodologies remain a challenge. This study employs a comprehensive approach, integrating Socio-economic, and Biophysical (SEBP), and the Five Capitals Model analyses encompassing human, social, physical, natural, and financial capital. The study employs factor analysis for mixed data (FAMD), cluster analysis using partitioning around the medoids (PAM) and univariate and bivariate techniques to identify and classify distinct typologies of smallholder farming systems in Senegal's Tambacounda and Sedhiou regions in 2020. A probit regression model gauges CSA adoption probability, to better focus CSA efforts. Results underscore the pivotal role of SEBP factors in shaping distinct farmer typologies, enabling precise CSA targeting. Geographical distribution patterns of these typologies reveal non-random clustering, particularly in specific regions. Four farmer typologies emerge: Cluster 1 (Sedhiou, low-income, high climate challenges), Cluster 2 (Sedhiou and Tambacounda, low-to middle-income, moderate climatic challenges), Cluster 3 (Tambacounda, high income, favorable climate), and Cluster 4 (Tambacounda, low income, severe climate challenges). Technology mismatches emerge between farmers' SEBP profiles and capital assets, prompting the identification of relevant technologies for soil fertility restoration and increased output. These findings highlight the importance of implementing CSAs in accordance with specific requirements, such as enhancing soil fertility, yield, and nutritional quality. A contextual understanding of local agricultural dynamics is likewise necessary for optimizing intervention strategies, according to the study.

1. Introduction

Farming systems in developing countries face challenges such as population growth, urbanization, land degradation, and demands for higher agricultural productivity; to address these challenges, innovations must urgently focus on climate change adaptation and mitigation, smallholder farmers' livelihoods, and food security [1,2]. Smallholder farming systems are highly varied, with

* Corresponding author.
E-mail addresses: karokicyrus@gmail.com (C. Muriithi), c.mwongera@ifad.org (C. Mwongera).
[1] These authors contributed equally to this work.

https://doi.org/10.1016/j.heliyon.2023.e20526
Received 16 June 2023; Received in revised form 25 September 2023; Accepted 27 September 2023
Available online 29 September 2023

agroecological zones, climate regimes, social groups, gender dynamics, and land uses all playing a crucial role [3]. Improved agricultural technology uptake and impact can be achieved through innovative mixed methods strategies focusing on context-relevant biophysical and socio-economic variables [4]. Mwongera (2019) advocates for customized approaches in the form of CSA to bolster production, resilience, and mitigation [5]. Notenbaert (2017) emphasize that CSA, through on-farm (composting, intercropping) and off-farm (carbon financing, market efficiency) strategies, is pivotal for achieving food security and climate targets [6].

According to Upadhaya (2021), the categorization of farmers has proven valuable in examining the impact of non-economic and imperceptible factors, such as attitudes and motivations, on farmer behavior and their reactions to various situations [7]. Geographical and temporal factors significantly affect agricultural productivity, as shown by Notenbaert et al. (2009) such that certain regions'

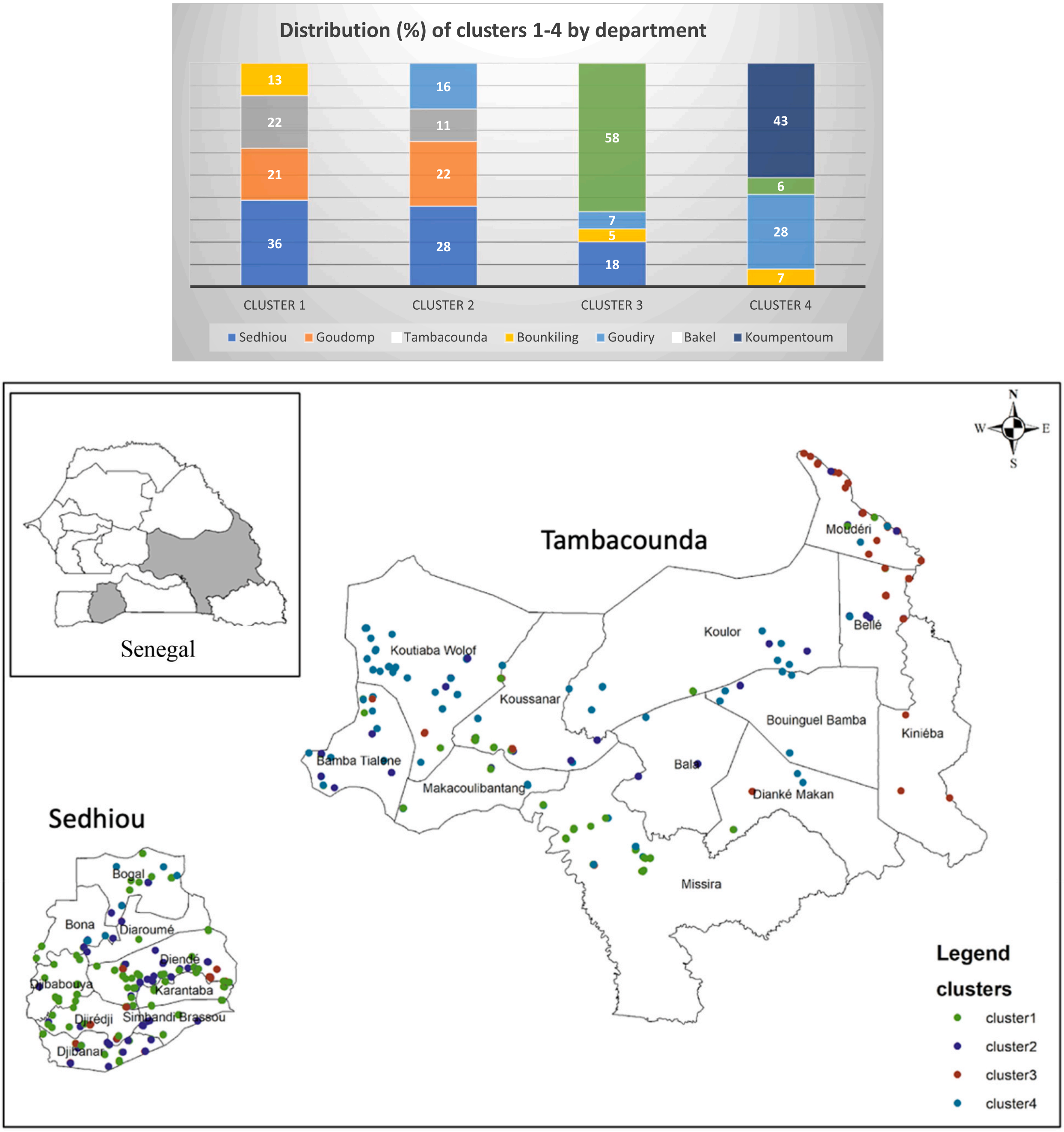


Fig. 1. Fig. 1a Distribution (%) of each farmer cluster by department.
Fig. 1b Spatial distribution of farmer clusters by arrondissement. The geospatial administrative layer was extracted from GADM (2022) maps and data.

agroecological attributes favor rain-fed crops, while others necessitate irrigation or grazing [8].

Unraveling farmer diversity via typologies is crucial for assessing agricultural households' capacity to enhance productivity [9]. Farmer characterization involves grouping diverse livelihoods and socioeconomic statuses into clusters based on shared traits. These typologies aid in comprehending local farming systems [10], land use, intensification technology adoption, climate resilience, and environmental assessments [11].

Studies have been conducted with an aim to refine farmer typologies. By linking local farm infrastructure and livelihood practices, farming household typologies are delineated [12], enabling targeted interventions based on types. Le Page (2014) identified three fundamental farming family groups through rice companion modeling, considering agroecological factors, techniques, and socio-economic approaches [13]. Wezel (2014) extensively explored agricultural system typology evolution, incorporating environmental variables [14].

Orounladji (2022) conducted an extensive investigation into the guinea fowl farming system. These findings not only shed light on the diverse aspects of guinea fowl farming in Benin, but also led to the identification of four distinct typologies of farmers [15]. These typologies were delineated according to factors such as geographical location, gender, educational background, undertaken activities, and incubation methods. The study further emphasized the importance of a comprehensive grasp of both phenotypic and molecular traits of the guinea fowl species in order to fully harness its potential.

In Abidjan, Konmy (2023) identified three distinct rabbit farming typologies, differing in breeding parameters and labor sources [16]. Their categorization employed cage investment, watering system design, and female breeder quantity. However, the lack of vital agricultural records, particularly financial data, posed a significant obstacle to the typology development, despite explaining differences from the present study.

Leveraging SEBP geographical data for targeting natural resource management, economic development, and poverty reduction is increasingly prevalent. Recent instances of prioritizing tasks based on development domains or spatial suggestions i.e. geographical units anticipating similar agricultural challenges or prospects underscore this trend [17].

Research on farmer typology seeks to categorize farmers by combining biophysical and socio-economic variables. Biophysical typology focuses on production elements, while socio-economic typology considers factors shaping smallholders' decisions. Past studies have identified systematic variations between defined farmer types. Some employed SEBP variables for cluster analysis to describe farming and livelihood systems. Yet, this research area has potential for further progress. Our study aims to enhance SEBP-based farmer typologies for targeted CSA technology and intervention scaling.

This study contributes by analyzing the impacts of diverse Capital Assets (human, natural, financial, social, and physical) on livelihood outcomes, which aids targeted CSA practices and farm characterization [18]. Chambers & Conway (1992) highlight sustainable livelihoods' resilience and resource preservation [19]. Bebbington (1999) underscores asset protection and conversion [20]; investigating rural strategies for resource conservation, transferability of successful capital holdings, and potential compensatory effects among capital types also enhances understanding [21].

This study seeks to develop a method for characterization of farmers that takes into account both their homogeneity and heterogeneity (within defined typologies or clusters) so that CSA solutions may be targeted more effectively and scaled more effectively among smallholder farmers. Doing so can reveal the diversity of smallholder farmers who may be differentially receptive to different CSA technology. This characterization can support: (i) better targeting of CSA implementation among smallholder farmers; (ii) targeting specific CSA technologies to homogeneous clusters of farmers; and (iii) a focus on proper bundling of CSA technologies that improve farmer households' Capital Asset endowments. These endowments include their natural capital, which supports household resilience for sustainability and resilience to climate change impacts.

2. Materials and methods

2.1. Study area

The study was conducted in Senegal's Sedhiou and Tambacounda regions, with Sedhiou located in the Casamance natural area in southwest Senegal (Fig. 1b). These two regions are the targeted zones of the Adaptation and Valorization of Entrepreneurship in Irrigated Agriculture (AVENIR), a project strategically designed to empower women and young farmers within the realm of agriculture. Subsistence rice farming, practiced particularly by women using traditional methods, is predominant in lowland areas of Sedhiou due to the ideal soil and climate conditions. However, factors such as decreased precipitation, protracted droughts, and soil degradation (salinization, acidification, and silting up) increasingly threaten the region's rice production systems. As a result, the Senegalese government and donors have begun promoting lowland recovery to ensure smallholder rice production [22]. Tambacounda Region in the Sahelian plains of eastern Senegal is the country's largest region. Local farmers in Tambacounda face challenges in marketing products due to low productivity levels, limited processing capacity, and challenging transport and storage conditions. This region, along with the eastern part of the country, also experiences high malnutrition rates and significant migration pressure, particularly towards Europe3.1.

2.2. Sampling procedure and data collection

This study was approved by the Institutional Review Board of The Alliance of Bioversity and CIAT, with ethics approval reference #2019-IRB30. The selection of sampling framework was based on the latest Senegalese General Census of Population and Housing, Agriculture and Livestock conducted by the National Agency of Statistics and Demography in 2013, which also informed the appropriate stratification level, which we confirmed as the department [23]. This sampling frame guided us toward the multi-stage sampling design for the selection of survey respondents. Individual households were the target unit for the survey. Cochran's sampling formula [24] was used to calculate a representative sample size, sampling power, level of effect sizes, and error rates. Out of 692 villages, 107 were randomly selected in Sedhiou, while 108 villages out of 1061 were randomly selected in the Tambacounda region. In each village, seven farming households were randomly selected via systematic sampling. Five of these had to include an eligible woman aged 35 years and above, and two households had to include an eligible younger person aged 18–34 years to be retained in the sample. Informed consent was obtained from all participants, as approved by The Alliance's Institutional Review Board for Human Subjects, and was also recorded electronically using the designated data collection tool as needed. In instances where a participant declined to participate, they were thanked for their consideration, and it was emphasized that their decision would not result in any prejudice. For participants who agreed to participate, they were thanked, and the intervi ew process was carried out accordingly. A balanced matched sample of 824 smallholder farmers was obtained from these households using 1:1 propensity score matching (PSM) which is a statistical technique that estimates treatment effects by pairing treated and control units with similar covariate-based propensity scores, reflecting treatment likelihood prediction.

We define a household as a person or group of persons who live together in the same house or compound, share the same housekeeping arrangements, and are catered for as one unit, meaning they commonly provide and share food [25]. The household head (*chef de ménage*) is regarded as the overall decision maker on land use and is instrumental in the approval of access of target respondents and survey administration.

The data for the study was collected in the field using the SurveyCTO digital data collection tool. SurveyCTO serves as a mobile data collection platform tailored for researchers and professionals operating across offline and online environments, offering user-friendly, secure, and scalable capabilities. A team of 45 trained enumerators and supervisors collected data in the Sedhiou and Tambacounda regions. The principal household members were identified with the help of local contacts like the Regional Director of Rural Development (DRDR) or village and household heads, and interviews were conducted with them. Interviews typically lasted around 1 h (±30 min) and were carried out by a single enumerator, with a single respondent, usually the principal woman or young farming member of each household.

The variables data were collected on included household demographics, farm characteristics, management, production, amount and sources of income, uptake of promoted interventions, perceptions and sources of information regarding those interventions, distance to markets and agricultural input suppliers, attitudes toward farming, gendered control of production, and food security indicators such as dietary diversity and food availability [26].

2.3. *Clustering analysis*

Unsupervised learning for dimensionality reduction created the variable used to develop the farmer typologies or clusters as defined in our study (Appendix: Table A1). By combining different statistical approaches, namely factor analysis for mixed data (FAMD) [27,28] and Partitioning Around the Medoids (PAM) clustering, we classified farmers into distinct homogenous clusters with similar SEPB characteristics and other similar exogenous factors such as livelihood capitals. FAMD—a principal component method dedicated to analyzing a data set containing quantitative and qualitative variables [29,30]—was used to reduce dimensionality and generate key indices [29]; it also made it possible to analyze similarities between individuals by considering a variety of variable types. In addition, correlation analysis was carried out on some of the variables' subsets to determine the correlation of different variables. Both the FAMD and correlation analysis aimed to transform a linearly higher original set of variables into fewer uncorrelated variables without losing significant information before the clustering process [31].

Cluster analysis began by using daisy functionality to estimate the distance between two points considering the mixed data type. Next, a visualization of similar and dissimilar observations based on the computed distances was created. Before running the cluster analysis, the optimal number of clusters was calculated using silhouette, gap stat, and within sum of squares (WSS), which gives a visual range of the optimal number of clusters needed to estimate the distinctiveness [32].

After determining the optimal validated number of clusters for analysis, PAM or k-medoids were applied to find a sequence of centrally clustered objects called medoids that were then placed into a set of selected objects. The algorithm minimized the average dissimilarity of objects to their closest selected object. PAM maps a distance matrix into a specified number of clusters and allows clustering according to specified distance metrics. PAM is particularly useful for this study as it is less sensitive to outliers and can handle mixed data [28].

Univariate and bivariate analysis coupled with statistical significance tests helped to determine the similarities and dissimilarities within and between clusters, providing optimal, highly defined cluster characterization. Indicators used to estimate nutrition and food security included (i) Food Consumption Score (FCS); (ii) Food Expenditure Share (FES); (iii) Household Dietary Diversity Score (HDDS); and (iv) Household Food Insecurity Access Scale (HFIAS). The scoring threshold categories for the FCS were as follows: (i) poor: 0–21, (ii) borderline: 21.5–35, and (iii) acceptable: >35. Additionally, we applied the Five Capitals Model [18], a framework of sustainability used to gain insights into the rural livelihoods of the farmers in each cluster in terms of sustainability and rural poverty [20]. These capitals include human, social, financial, natural, and physical capital. Appendix: Table A2 indicates the variables used for the analysis, including the Cronbach alpha for data reliability and internal consistency test score and Kaiser-Meyer-Olkin (KMO) to measure how suited the data is for factor analysis.

To estimate the likelihood of adoption, we used a general probit regression model below [33] to assess how covariates (cluster and capital assets) vary with differently grouped CSA technologies.

Below is the estimated probit model regression:

$$CSA_i = \alpha + \beta_i Cluster_i + \beta_i Capital\ index_i + \varepsilon_i \tag{1}$$

The dependent variable (CSA_i) is a dummy representing grouped CSA practices. $Cluster_i$ is a cluster classification variable with values of 1, 2, 3, or 4 denoting the cluster to which a single household has been assigned. $Cluster_1$ 1 consists of low-income farmers who have high climate-related agricultural challenges, $Cluster_1$ 2 are low-to mid-income farmers with moderate climate-related agricultural challenges, $Cluster_1$ 3 are highest income farmers with good climate conditions for agriculture, and $Cluster_1$ 4 are lowest income farmers with highest climate-related agricultural challenges. $Capital\ index_i$ represents human, social, financial, natural, and physical capital indexes. A, β_i, and β_i are estimated parameters, and ε_i is the random error term.

3. Results

3.1. Description

Fig. 1a and b presents the quantitative and spatial distribution of each identified clusters in the regions of Sedhiou and Tambacounda, by department. The farmers in Cluster 1 represent 36% of the sampled farmers. A large majority of them came from the Sedhiou department (36%), Goudomp department (21%), Tambacounda (28%), and Bounkiling department (13%). The farmers in Cluster 2 represent 24% of the sampled farmers; a large majority of them came from the Sedhiou department (28%), Goudomp department (22%), Goudiry (16%), and Tambacounda (11%). The farmers in Cluster 3 represent 15% of the sampled farmers; a large majority of them came from the Bakel department (58%), Sedhiou department (18%), Goudiry (7%), and Bounkiling (5%). The farmers in Cluster 4 represent 25% of the sampled farmers, with a large majority of them coma from the Koumpentoum department (43%), Goudiry (28%), Bounkiling (7%), and Bakel 6%.

3.2. Characterization using SEBP

We analyzed the homogeneity and heterogeneity of these clusters by varying them with different SEBP factors. Results are presented in Table 1. Over 70% of smallholder farmers in Cluster 1 (low-income, high climate-related agricultural challenges) are from Sedhiou region. Farmers in Cluster 2 (low-to mid-income, moderate climate-related agricultural challenges) are from the regions of Sedhiou (55%) and Tambacounda (45%). In Cluster 3 (highest income, good climate conditions for agriculture), 75% of farmers are from Tambacounda region. In Cluster 4 (lowest income, highest climate-related agricultural challenges), over 92% of smallholder farmers are from Tambacounda region (see Fig. 2).

The characterization analysis for the different clusters also includes the farmers' food and nutritional security conditions, as shown in Table 1. The higher the FCS, the greater the dietary diversity and the frequency of food consumed; a high FCS increases the likelihood that a household achieves nutrient adequacy. The FES measures household economic vulnerability and is used as an indicator of household food security. We categorized households into four groups according to their food expenditure share in the past 30 days. HDDS is used to assess the dietary quality and quantity generated using 12 food groups. The higher the score, the higher the dietary quality. HFIAS indicates experience in household food insecurity. The HFIAS value ranges from 0 to 27. An HFIAS of zero indicates that the household is food secure, and an HFIAS of 27 indicates the household is experiencing severe food insecurity.

3.2.1. Cluster 1: low-income, high climate-related agricultural challenges

Farmers in this cluster experience the lowest elevation (low altitude) of 565 m above sea level (ASL), the lowest mean annual amount of rainfall of 392 mm, and the highest mean temperature of 24 °C. The land is characterized by an average pH of 7.38. 73% of these farmers are in the low-wealth quintile, with 25.3% in the middle-wealth quintile and only 1.7% in the high-wealth quintile. Farmers in this cluster received the lowest amount of remittance income, at FCFA 67,051, and the lowest agricultural income, at FCFA 143,108, while the average income from other sources was FCFA 757,507 (Appendix: Table A3).

As shown in Table 2, the top irrigation technologies used by farmers in Cluster 1 are pouring water by hand using a container (43.5%), using a bucket (22.9%), and using irrigation canals (11.8%). No farmer from Cluster 1 used drip irrigation, while gravity-fed irrigation (1.8%), irrigation using electric or diesel pump (2.4%), and pipe irrigation (2.9%) were the least used technologies (Appendix: Table A3).

This study indicates that 84% of farmers in Cluster 1 fall into the poor FCS category, 15.3% fall into the borderline category, and only 0.7% fall into the acceptable category. In addition, 68.7% of farmers are classified as having low FES, indicating poor food security, while 17.4% were classified as having moderate FES. Only 7.8% of farmers were classified as having high and 6% extremely

Table 1
Distribution of farmers in different clusters by region.

Cluster	1	2	3	4	Overall P-value	
Region (%)	Sedhiou	(70.3)	(55.3)	(25.0)	(7.8)	<0.001
	Tambacounda	(29.7)	(44.7)	(75.0)	(92.2)	<0.001
Total observations	(n = 824)	300	199	120	205	

Notes: n values are presented with column percentages in parentheses: P-values indicate the likelihood that the null hypothesis (there if no difference or the difference is equal to zero) is correct given the sample data.

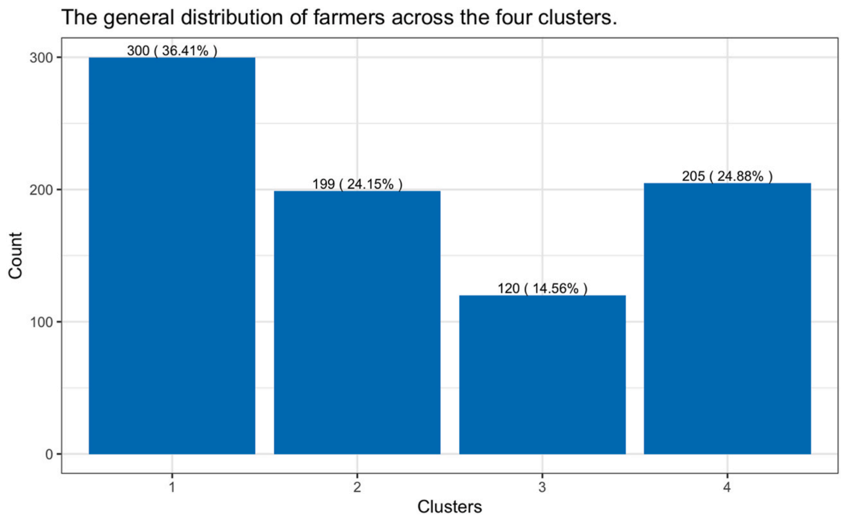


Fig. 2. Number of farmers per cluster. (Matched Sample size of 824 women and youths).

Table 2
Irrigation technologies used by farmers in different clusters.

	Percentage of farmers by clusters				
Irrigation technologies (%)	1	2	3	4	Overall p-value
Basin dug around plant	(3.5)	(0.6)	(4.4)	(0.0)	<0.001
Bucket	(22.9)	(35.2)	(8.0)	(43.5)	
Drip	(0.0)	(0.0)	(0.9)	(0.0)	
Electric or diesel pump	(2.4)	(0.6)	(23.1)	(13.0)	
Gravity-fed (river diversion)	(1.8)	(3.2)	(5.3)	(0.0)	
Irrigation canals/channel	(11.8)	(2.9)	(16.9)	(0.0)	
Pipe	(2.9)	(0.3)	(15.6)	(4.3)	
Pouring water by hand (using container)	(43.5)	(51.6)	(15.1)	(30.4)	
Sprinkler	(11.2)	(5.6)	(10.7)	(8.7)	
Total Observations (n = 759)	*170*	*341*	*225*	*23*	

Notes: n values (number of farmers who practice any form of irrigation) are presented with column percentages in parentheses. P-values indicate the likelihood that the null hypothesis (there if no difference or the difference is equal to zero) is correct given the sample data.
Thus, in this cluster, farmers reside in low-altitude, arid areas with alkaline soil. Mostly low-income, they rely on manual irrigation and face severe food insecurity, marked by poor FCS and low FES scores, indicative of limited dietary access.

high FES, indicating good food security. The average HFIAS for Cluster 1 farmers was 3.93, and their average HDDS was 5.9 out of the possible 12 scores (Appendix: Table A3).

3.2.2. Cluster 2: low-to mid-income, moderate climate-related agricultural challenges

Farmers in this cluster experience the lowest elevation (low altitude) of 688 m ASL, a low mean annual rainfall of 526 mm, and a mean temperature of 23.4 °C. The land is characterized by an average pH of 7.07. In Cluster 2, 74% of farmers are in the low-wealth quintile, 23.3% are in the middle-wealth quintile, and only 3% are in the high-wealth quintile. The farmers in this cluster received a low amount of remittance income (FCFA 75,756) and a low agricultural income of FCFA 170,287, while the average income from other sources was FCFA 737,171 (Appendix: Table A3).

As shown in Table 2, the main irrigation technologies used by farmers in Cluster 2 are pouring water by hand using a container (51.6%) and using a bucket (35.2%), while no farmer used drip irrigation, and all other technologies were used by between 1% and 6% of the farmers (Appendix: Table A3).

In Cluster 2, 92% of farmers fall into the poor FCS category, 8% fall into the borderline category, and 0% fall into the acceptable category of adequate food intake. 75.9% of farmers fall into the low FES category, followed by 9.5% in the moderate category, 7% in the high category, and 7.6% in the very high category. Their average HDDS is 4.66, while their average HFIAS is 4.30 (Appendix: Table A3).

Cluster 2 farmers occupy low-altitude, arid regions with alkaline soil, mostly low-income and reliant on manual irrigation. These conditions contribute to pronounced food insecurity, evident in poor FCS, low FES, HDDS, and HFIAS scores.

3.2.3. Cluster 3: highest income, good climate conditions for agriculture

Farmers in this cluster experience an elevation (high altitude) of 1038 m ASL, a high mean annual rainfall of 911 mm, and a low mean temperature of 21 °C. The land is characterized by an average pH of 6.12. 37.5% of these farmers are in the low-wealth quintile, 24.2% are in the high-wealth quintile, and only 38.3% are in the middle-wealth quintile. The farmers in this cluster received a high amount of remittance income (FCFA 173,033), a high agricultural income of FCFA 224,413, and the highest average income from other sources received is FCFA 1,434,134 (Appendix: Table A3).

As shown in Table 2, farmers in Custer 3 used the following watering techniques: electric or diesel pumps (23.1%), irrigation canals or channels (16.9%), pipes (15.6%), pouring water by hands (15.1%), and sprinklers (10.7%) (Appendix: Table A3).

In Cluster 3, only 0.8% are in the acceptable FCS category, 8.3% are in the borderline FCS category, and 90.8% are in the poor FCS category. In terms of FES, 53.6% of farmers fall into the low category, 17.9% into the moderate category, 9.8% into the high category, and 18.8% into the very high category. Their HDDS on average is 4.11, while their HFIAS on average is 3.98 (Appendix: Table A3).

Cluster 3 farmers thrive in high-altitude regions with favorable pH, balanced wealth distribution, advanced irrigation methods, and substantial income diversity. However, prevalent poor FCS and low FES categories, along with limited dietary diversity, underscore persistent food security challenges.

3.2.4. Cluster 4: lowest income, highest climate-related agricultural challenges

Farmers in this cluster experience an elevation (high altitude) of 1132 m above sea level (ASL), a high mean annual rainfall of 913 mm, and a low mean temperature of 21 °C. The land is characterized by an average pH of 6.09. 82% of these farmers are in the low-wealth quintile, 2.9% are in the high-wealth quintile, and only 15.1% are in the middle-wealth quintile. The farmers in this cluster received the lowest amount of remittance income (FCFA 11, 617) and the lowest agricultural income of FCFA 60,063, and the lowest average income from other sources was FCFA 519,080 (Appendix: Table A3).

As shown in Table 2, the top irrigation technologies used by farmers in Cluster 4 are a bucket (43.5%), pouring water by hand using a container (30.4%), and using a sprinkler (8.7%) (Appendix: Table A3).

In Cluster 4, 99% are in the poor FCS category, 1% in the borderline FCS category, and 0% in the acceptable FCS category. 47.8% of farmers are in the low category, 30.6% are in the moderate category, 14.6% are in the high category, and 7% are in the very high category. Their average HDDS was 2.47, while their average HFIAS was 7.53 (Appendix: Table A3).

Cluster 4 farmers reside in high-altitude regions with significant rainfall and modest pH. Predominantly low-income, they employ basic irrigation methods and face alarming food insecurity, as reflected by their poor FCS and low FES status, accentuated by low HDDS and elevated HFIAS scores, indicating vulnerability and constrained dietary options.

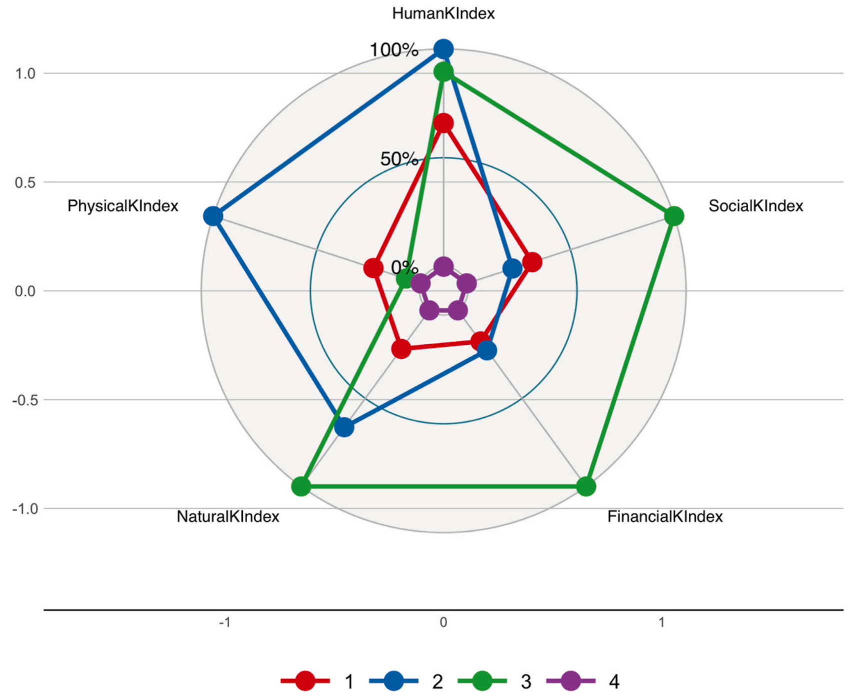


Fig. 3. Spider plot indicating levels of normalized capital scores of livelihoods by clusters. (KEY WORD: HumanKindex – human capital index, SocialKindex – social capital index, FinancialKindex – financial capital index, NaturalKindex – natural capital index, PhysicalKindex – physical capital index).

3.3. Capitals

To understand the 4 clusters, we further use the Five Capital Model of livelihood. Although the definition of the five capitals varies [34,35], in this analysis, they are defined as (1) human capital, (2) social capital, (3) physical capital, (4) natural capital, and (5) financial capital [18], as indicated in (Appendix TableA2). This table also includes two test scores: (i) the Cronbach's alpha test, which measures the reliability or internal consistency of the indicators used, and (ii) the Kaiser-Meyer-Olkin (KMO) test, which measures sampling adequacy to indicate if our samples are suitable for generating the capital composite indices using FAMD. We constructed a composite index (from several indicator variables: Appendix: Table A2) using a FAMD for each of the five capitals [36].

Fig. 3 indicates the distributions of clusters across the five capitals. In the diagram, farmers in Cluster 3 (green) are characterized by the highest social, financial, and natural capital level and a slightly high (above 50%) level of human capital. Farmers in Cluster 4 are characterized by the lowest level of all the five capitals. Farmers in Cluster 2 are characterized by the highest level of physical and human capital and a slightly higher level of natural capital. In Cluster 1, farmers are characterized by more human capital and less physical, natural, financial, and social capital.

3.4. Adoption

We used an approach by Paudel et al. (2017) [37], who defined CSA technology as practices or technologies that support at least one of the three pillars of CSA - Productivity, Resilience, and Mitigation in an agriculture subject to climate change and variability. The authors group CSA technologies as follows: (i) water-smart technologies that improve water usage efficiency: water channels and irrigation technologies, rainwater harvesting, community water management, laser land leveling, water conservation, drip irrigation, and on-farm water management strategies; (ii) seed-smart technologies used to improve harvests by developing climate resilient seed types, using seed selection procedures, and enhancing seed types or short-duration crop varieties; (iii) knowledge-smart technologies that combine science and local knowledge to enhance processing, integrate pest control, and develop contingency crop planning; (iv) carbon smart interventions that reduce greenhouse gas emissions: agroforestry, livestock and manure management, intercropping, and green manuring; and (v) nutrient smart interventions that improve nutrient use efficiency and include site-specific integrated nutrient management, green manuring, and legume intercropping [2,37].

The analysis shows that the adoption potential for CSA practices varies significantly across farmer clusters. From the regression results in Table 3, we see a significant positive relation between farmers in Cluster 2 and the adoption of seed-smart CSA technologies compared to the Cluster 1 farmers. Farmers in Cluster 3 are less likely to adopt carbon and nutrient smart CSA technologies and have a higher likelihood of adopting seed and water smart CSA technologies than Cluster 1 farmers. Farmers in Cluster 4 are more likely to adopt carbon smart technologies and less likely to adopt knowledge and water smart technologies than those in Cluster 1.

We also note the positive and negative relationship between the five capitals and the adoption of CSAs. Financial capital plays an important role in modern society, enabling other types of capital to be owned and traded. It has a positive relationship (significant at alpha = 0.1) with the adoption of carbon and nutrient-smart CSA technologies and a negative relationship with the adoption of water-smart technologies.

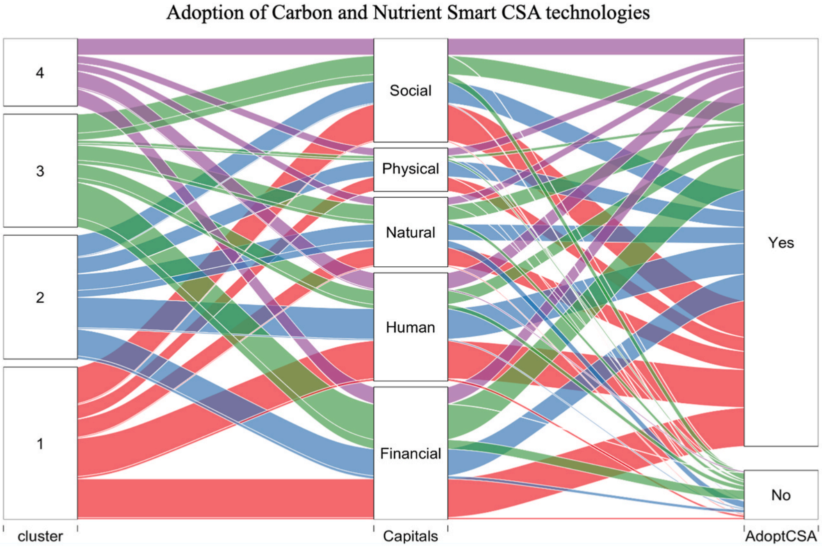
Any stock or flow of energy and materials that create products and services is considered natural capital. It is the foundation of not just production but also family and societal life. Therefore, adopting knowledge-based smart technology is positively related to increased household natural capital growth.

Fig. 4 illustrates all the possible pathways from clusters to levels of capital to adoption—by which farmers in different clusters with different degrees of capital adopt CSA technology. The farmers are represented as follows: Cluster 1 in red (low-income, high climate-related agricultural challenges); Cluster 2 in blue (low to mid-income, moderate climate-related agricultural challenges); Cluster 3 in green (highest income, best agricultural climate); and Cluster 4 in purple (lowest income, highest climate-related agricultural

Table 3
Probit regression results: Grouped technologies.

	Dependent variable:							
	Carbon and nutrient smart	SE	Knowledge smart	SE	Seed smart	SE	Water smart	SE
Cluster 1	Reference							
Cluster 2	−0.119	(0.165)	0.241	(0.164)	0.724**	(0.302)	0.332*	(0.172)
Cluster 3	−1.230***	(0.170)	0.204	(0.199)	1.873***	(0.287)	1.512***	(0.179)
Cluster 4	0.673***	(0.231)	−0.824***	(0.287)	−3.457	(175.851)	−0.509**	(0.239)
Human Index	0.127	(0.228)	−0.151	(0.246)	−0.684	(0.605)	0.032	(0.189)
Social Index	0.888	(0.645)	0.264	(0.387)	−0.339	(0.522)	−0.81	(0.618)
Financial Index	0.984*	(0.505)	0.092	(0.327)	0.482	(0.299)	−1.088*	(0.567)
Natural Index	−0.085	(0.160)	0.443**	(0.187)	0.086	(0.185)	−0.029	(0.182)
Physical Index	0.096	(0.164)	−0.16	(0.221)	−0.038	(0.169)	−0.736	(0.843)
Constant	1.267***	(0.126)	−1.540***	(0.124)	−2.453***	(0.263)	−1.420***	(0.139)
Observations	824		824		824		824	
Log Likelihood	−236.691		−192.792		−115.259		−220.608	
Akaike Inf. Crit.	491.383		403.583		248.517		459.215	

Notes: SE – Standard Error, * means significantly different at 10%, ** means significantly different at 5%, *** means significantly different at 1%.



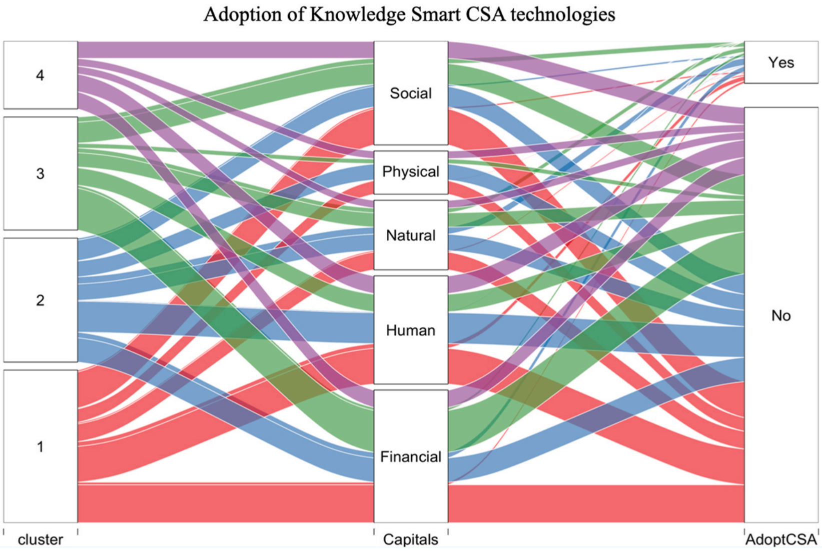


Fig. 4. aAlluvial plot of adoption helps us visualize the flow of data (from clusters to adoption of CSA) across capital variable. This diagram beautifully illustrates what clusters adopted and did not adopt carbon and nutrient smart CSA technologies.
Fig. 4bAlluvial plot of adoption helps us visualize the flow of data (from clusters to adoption of CSA) across capital variable. This diagram beautifully illustrates what clusters adopted and did not adopt knowledge smart CSA technologies.
Fig. 4cAlluvial plot of adoption helps us visualize the flow of data (from clusters to adoption of CSA) across capital variable. This diagram beautifully illustrates what clusters adopted and did not adopt seed smart CSA technologies.
Fig. 4dAlluvial plot of adoption helps us visualize the flow of data (from clusters to adoption of CSA) across capital variable. This diagram beautifully illustrates what clusters adopted and did not adopt water smart CSA technologies.

challenges). Most farmers applied carbon and nutrient-smart practices regardless of capital or cluster. The use of water and seed-smart technology use correlates closely with farmers with high incomes and suitable environments (Cluster 3) and high endowments of social and financial capital.

Fig. 4a, b, Fig. 4c and d shows that farmers in Clusters 1 and 2, with their financial, human, and natural capital endowments, have historically adopted carbon and knowledge-smart CSA technologies. In contrast, Cluster 3 farmers, endowed with robust social, natural, human, and financial capitals, have historically adopted water and seed and breed CSA technologies. Cluster 4 farmers, with their characteristic financial, natural, and social capital endowments, have historically adopted carbon and nutrient smart CSA technologies.

As shown in Fig. 5, the adoption of agricultural practices varies across different clusters. Most farmers in Cluster 1 practice crop rotation, fallow, minimum tillage, agroforestry, and intercropping. The common agricultural practices by farmers in Cluster 2 include

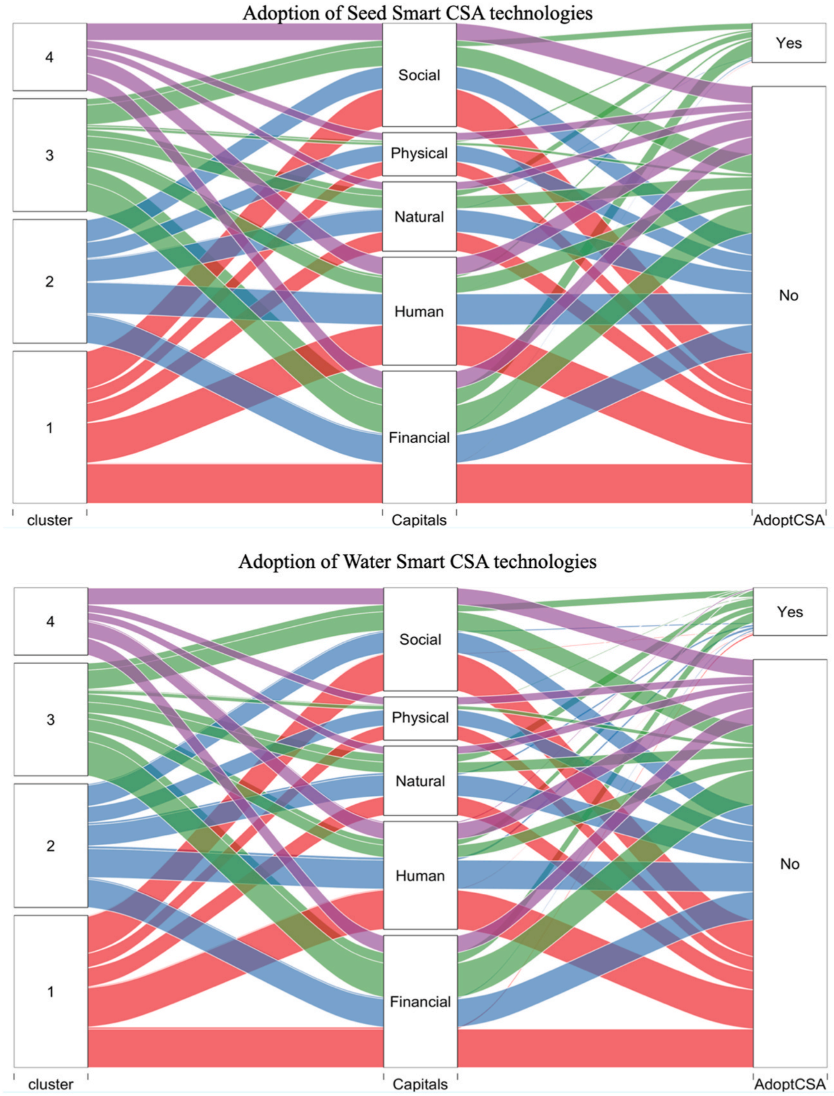


Fig. 4. (*continued*).

minimum tillage, farrow, crop rotation, and agroforestry. Notable common agricultural practices by farmers in Cluster 3 include flood irrigation and farmyard manure, and common practices among the farmers in Cluster 4 are crop rotation, fallow, and intercropping.

These findings suggest that adoption differs by cluster. Cluster 1 predominantly employs crop rotation, fallow, minimum tillage, agroforestry, and intercropping. In Cluster 2, common practices encompass minimum tillage, farrow, crop rotation, and agroforestry. Flood irrigation and farmyard manure stand out in Cluster 3, while Cluster 4 farmers often utilise crop rotation, fallow, and intercropping.

4. Discussion

4.1. Validity

The reliability analysis results (Appendix: Table A2) indicate that most data used are reliable and valid. Cronbach alphas were below 0.7, indicating a low internal consistency of data (inter-relatedness of the items). According to Tavakol and Dennick (2011), the number of test items, item inter-relatedness, and dimensionality affect the alpha value [38]. There are different reports about the acceptable alpha values, ranging from 0.70 to 0.95 [39–41]. A low alpha value could be due to a low number of questions, poor inter-relatedness between items, or heterogeneous constructs. For example, some should be revised or discarded if a low alpha is due to poor correlation between items. If an alpha is too high, it may suggest that some items are redundant as they test the same question in a different guise. A maximum alpha value of 0.90 has been recommended [42].

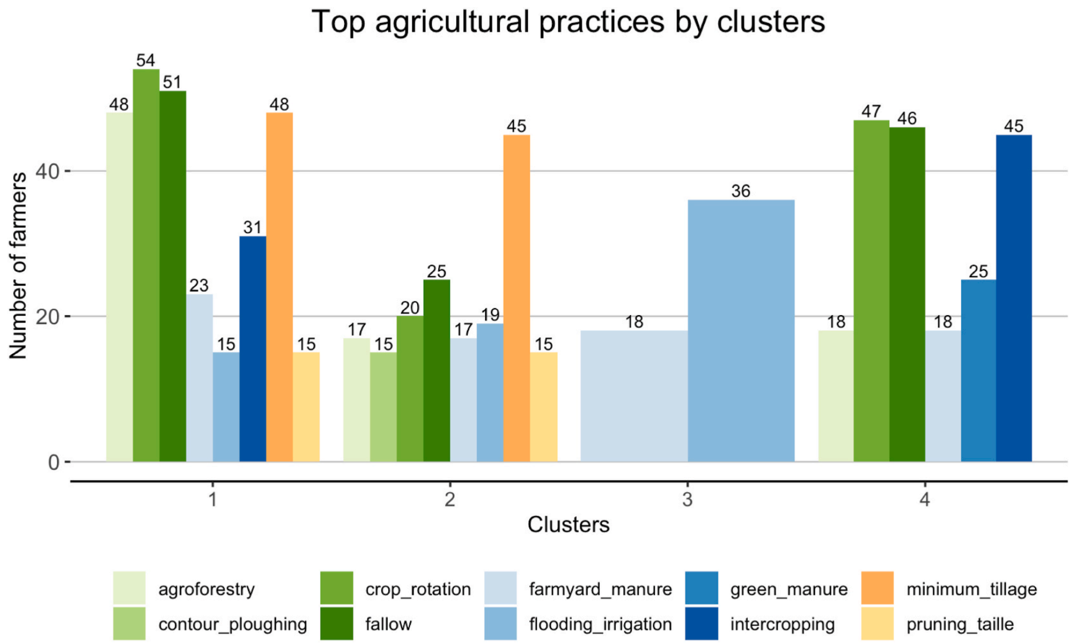


Fig. 5. Top agricultural practices by clusters.

The overall measure of sampling adequacy (KMO test) for the FAMD was between 0.5 and 0.56, which puts it into the miserable range. In this case, the results of each procedure indicate the data is generally appropriate for factor analysis but not very adequate. According to Dziuban and Shirkey (1974), using sampling adequacy measurements allows for decisions regarding individual variables and determining the overall quality of the analysis [43]. By using the KMO index, the investigator may identify individual variables that might lead to erroneous interpretation. Because factor-analytic investigations require prior judgments concerning which variables should be included, measuring sampling adequacy might be a logical intermediate step to assessing the efficacy of those judgments. The low Cronbach alpha and KMO test scores could be attributed to our sample size.

4.2. Targeting

Combining SEBP factors to identify and estimate potential smallholder farmers' clusters was a successful approach for possible CSA targeting. Table 4 displays the relationship between agricultural practices, their underlying characteristics, and their impact on farmers' adoption behavior and production outcomes. This approach reveals the best CSA targeting method as it relies on biophysical factors or natural capital to differentiate the varying needs of farmers in similar clusters. For example, farmers in Clusters 3 and 4 are predominantly located in Tambacounda region (Fig. 1), characterized by high elevation and high amounts of rainfall. The likelihood of adoption varies between the two clusters. Though the main goal is to improve soil fertility and water use management, the farmers in Cluster 3 are likely to adopt seed- or breed-smart CSAs and water-smart CSA technologies. In contrast, farmers in Cluster 4 are likely to adopt carbon and nutrient-smart CSAs. Therefore, this approach helps us use SEBP factors and natural capital and choose appropriate CSA targets based on the likelihood of adoption and the problems the farmers in different clusters face.

There is also a need to bundle CSA technologies and develop participatory solutions with input based on representative cluster challenges. For example, farmers in Cluster 1 are likely to adopt knowledge- and water-smart technologies, which will allow them to recommend solutions that address issues such as nitrogen inefficiencies, fertility, and water use management. The likely CSA combination bundle for farmers in such clusters would be organic and inorganic fertilizers with improved crop varieties and cover cropping (Table 5).

To estimate natural capital in households, we examined crops, land, and soil characteristics: indicators of stock levels of natural ecosystems among the smallholder farmer households. We see that the natural capital index has a significant positive relationship with adopting knowledge-smart technologies. Farming activities and natural capital are inseparable and are gaining attention due to climate change and reduced production concerns. The agricultural practices that smallholder farmers apply directly influence the quality of natural capital and indirectly climate change. Farmers in Clusters 2 and 3 are endowed with high levels of natural capital, while farmers in Clusters 1 and 3 have low levels of natural capital, which can be indirectly linked to the different livelihoods of farmers in this cluster.

The soil condition for farmers in Cluster 1 is fertile based on a high cation exchange capacity (CEC) level, sandy, clay, and silt soil availability, and neutral soil pH levels. Our analysis shows farmers in this cluster use few organic and organic fertilizers and experience low rainfall amounts. Some of the practices common among these farmers are agroforestry, contour plowing, and leaving land fallow, and the main occupation of these farmers include crop and livestock farming. The farmers in this cluster are likely to adopt knowledge

Table 4
Summary of farmers' typologies, i.e., cluster characteristics.

Cluster		1	2	3	4
Region		Sedhiou	Sedhiou and Tambacounda	Tambacounda	Tambacounda
Biophysical	Elevation and rain	Low elevation (low land), low rainfall	Low elevation (low upland), average rainfall	High elevation, high rainfall	High elevation, high rainfall
	Nitrogen-responsible for root growth	Low nitrogen levels	Fair nitrogen levels	High nitrogen levels	High nitrogen levels
	Soil	Sandy, clay, and silt soil	Sandy and clay soil	Sandy and clay, low silt	Sandy and clay, low silt
	Soil Cation Exchange Capacity (CEC)-soil fertility	High CEC	Average CEC	Average CEC	Low CEC
Social-economic	Income	Average income levels	Average income levels	Highest income levels	Lowest income levels
	Education	Low levels of education	Low levels of education	Low levels of education	Lowest levels of education
	Occupation	Crop, livestock farming, and household chores	Crop and livestock farming	Crop and livestock farming	Crop and livestock farming
	Household type	Male-headed or female-headed households	Male-headed, joint household, or female-headship	Male-headed or joint household headship	Male-headed
	Social group	Producer group, religious group, Savings and credit group, civic group, and charitable group	Producer group, religious group, Savings and credit group, charitable group	Marketing or commercialization, agricultural producer, Irrigation water use association (IWUA), water user group, religious group	Producer group, religious group, Savings and credit group
Capitals		High in human and social capital, Low in physical, natural, and financial capital	High in human, physical, and natural capital Low in social and financial capital	High in human, social, financial, and natural capital Low in physical capital	Low in human, social, physical, financial, and natural capital
Practices		Agroforestry Contour plowing Crop rotation Fallow Minimum tillage	Minimum tillage Fallow	Farmyard manure Flood irrigation	Crop rotation Fallow Intercropping
Irrigation method		Pouring water by hand Bucket Irrigation canals Sprinkler	Pouring water by hand Bucket	Electric or diesel pump Irrigation channels Pipes Pouring water by hand	Bucket Pouring water by hand Electric or diesel pump Sprinkler
Adoption Sg – significant NSg – not significant	Carbon and nutrient smart	**- (Sg)**	**-(NSg)**	**-(Sg)**	+**(Sg)**
	Knowledge smart	+**(Sg)**	+**(NSg)**	+**(NSg)**	**-(Sg)**
	Seed or breed smart	+**(NSg)**	+**(Sg)**	+**(Sg)**	**-(NSg)**
	Water-smart	+**(Sg)**	+**(Sg)**	+**(Sg)**	**-(Sg)**
Production	Village access	Paved, gravel, and footpath	Paved, gravel, and footpath	Paved, gravel, and footpath	gravel and footpath
	Distance	Long distance to seed and product market	Long distance to seed and product market	Short distance to seed and product market	Short distance to seed and product market
	Fertilizer	Below-average use of organic and inorganic fertilizers	Average use of organic and inorganic fertilizers	High use of organic and inorganic fertilizers	Low use of organic and inorganic fertilizers
	Harvest	Average harvest, low-marketed product	Average harvest, low-marketed product	High-harvest, high-marketed product	Low-harvest, lo-marketed product
Nutrition		High FCS, High HDDS, Average FES Low HFIAS	Average FCS, Average HDDS, Low FES Low HFIAS	Average FCS, Average HDDS, High FES Low HFIAS	Low FCS, Low HDDS, Average FES High HFIAS

and water-smart CSA technologies that can boost nitrogen levels, improving plant root growth for increased production.

Farmers in Cluster 2 receive average rainfall amounts, and the soil is sandy and clay with neutral pH levels. Though there are higher nitrogen levels compared to Cluster 1, the soil CEC is average in Cluster 2 than Cluster 1. Common technologies applied in this cluster are fallow and minimum tillage, while the common occupations are crop and livestock farming, and farmers in this cluster are likely to adopt seed and water-smart CSA technologies. These technologies should boost soil fertility and raise nitrogen levels to boost

Table 5
Possible recommendation scenarios for CSA targeting by clusters.

Cluster	1	2	3	4
Problem/challenge	Improve nitrogen levels for root formation	Improve nitrogen levels for root formation		
	Maintain or improve high soil fertility (CEC)	Maintain and improve high soil fertility (CEC)	Improve soil fertility (CEC)	Improve soil fertility (CEC)
	Water use improvement due to low rainfall	Water use improvement due to low rainfall	Water use improvement due to heavy rainfall	Water use improvement due to heavy rainfall
	Maintain soil bulk density (porosity)	Maintain soil bulk density (porosity)	Improve soil bulk density (porosity)	Maintain soil bulk density (porosity)
	Maintain soil acidity	Maintain soil acidity	Reduce soil acidity	Reduce soil acidity
Likelihood of adoption	Knowledge smart	Seed and breed-smart	Seed and breed smart	Carbon and nutrient smart
	Water smart	Water smart	Water smart	
Specific practices (Paudel et al., 2017)	Improved/short-duration crop varieties	Improved/short-duration crop varieties	Improved/short-duration crop varieties	Agroforestry/Horticulture
	Green Manuring	Green manuring	Site-specific integrated nutrient management	Intercropping
	Organic and inorganic fertilizers	Organic and inorganic fertilizers		
	Integrated pest management	Integrated pest management		
	Contingent crop planning	Contingent crop planning	Contingent crop planning	Contingent crop planning
	Rainwater Harvesting- Farm Ponds	Rainwater Harvesting- Farm Ponds	Drainage Management	Drainage Management
	Drip Irrigation	Drip Irrigation	Drip Irrigation	Drip Irrigation
	Sprinkler Irrigation	Sprinkler Irrigation	Cover crops method	Cover crops method
	Cover crops method	Cover crops method		

productivity among farmers.

Farmers in Cluster 3 receive the highest amount of rainfall and have the highest harvest of tree and crop products. This cluster's sandy and clay soil characteristics are acidic, with average fertility and the highest nitrogen levels. Common practices include using farmyard manure, flood irrigation, and high levels of organic and inorganic fertilizer. However, despite good conditions for plant growth, the farmers in this cluster are likely to adopt seed and water-smart CSA technologies and less likely to adopt carbon and nutrient-smart technologies that would likely improve soil fertility (CEC).

Despite receiving high rainfall, the farmers in Cluster 4 experience low crop production. The sandy, clay, and low silt soils in this cluster are characterized as acidic and less fertile based on low CEC. The soils have high nitrogen levels despite the low use of inorganic and organic fertilizers. The farmers in this cluster are likely to adopt carbon and nutrient smart technologies and less likely to adopt knowledge- and water-smart technologies. Appropriate carbon and nutrient smart technologies are needed to maximize the high rainfall, maintain high nitrogen levels, and boost soil fertility.

This study underscores the pivotal role played by the five capitals of livelihood in molding farmers' adaptive capacity and consequently driving the adoption of CSA practices. The interplay among these capital characteristics directly influences a farmer's adaptive capacity. Human capital development equips farmers with essential knowledge and skills, while social capital facilitates the exchange of information and collaborative efforts. Adequate physical and natural capital provide the necessary resources for effective CSA implementation, and financial capital ensures the feasibility of investing in adaptable strategies. By harnessing and synergizing these capital elements, farmers can enhance their adaptive capacity, navigate climatic challenges more adeptly, and expedite the uptake of sustainable CSA practices.

Importantly, these insights extend beyond the study regions, offering valuable guidance for global contexts.

Abdul-Razak & Kruse (2017) found economic resources, training, and technology to be crucial for small farmers' adaptive capacity, while infrastructure, social capital, and institutions were less significant [44]. In Ghana, remittances from relatives living outside the communities signified the importance of family/community bonds in decreasing vulnerability to climate change since remittances play a significant role in lessening the burden associated with climate impacts. As noted by Kabobah et al. (2018), remittances from external relatives demonstrate the role of strong ties in reducing climate vulnerability [45].

4.3. Recommendation summary

Table 5 indicates the possible CSA technologies recommendation based on the challenges the farmers in different clusters face and the likelihood of adoption.

5. Conclusion

The primary purpose of this study was to offer techniques for identifying smallholder farmer typologies (or clusters) based on given SEBP factors for CSA technology targeting. Diverse smallholder farmer profiles face different agricultural and climatic issues, thus requiring tailored interventions and advice [46]. Thus, grouping farmers into relevant typologies or clusters enables better targeting and prioritization of CSA technology, research, and development for the members of such clusters. Clustering farmers using SEBP factors is important for target mapping, improving the adaptability and performance of individual clusters, determining potential opportunities and barriers to technology adoption, and ensuring the formulation of sector-specific policies, appropriate agricultural research, and the development of practical tools for the appropriate targeting of CSA technologies [47].

Among the Five Capitals of livelihood, natural capital has emerged as a key asset associated with adopting CSA technologies by farmers of various typologies. We ascribe this to the extent to which human activities, directly and indirectly, influence the management of natural household assets on their farms. This management, in turn, contributes to the exploitation or protection of these assets. More positive attitudes to natural capital can lead to changes in crop production, which can indirectly influence CC, impacting household livelihood and food security. Improving and conserving natural capital is critical for smallholder farmers to build sustainable and resilient livelihoods. These actions are linked to better soil conditions and fertility, successful crop development, and better CC resiliency.

As a result, research focused on elucidating potential challenges for smallholder farmer typologies or clusters related to natural capital, present coping mechanisms employed by these families, and the likely CSA proposal based on their likelihood of adoption. There is a strong belief that this study will provide insights into subjects of critical importance to the academic community and develop practical CSA targeting and scaling methods.

6. Limitation

In this study, the small sample size may have contributed to the low reliability measure and weak sampling adequacy. The limitation of the findings to one setting (baseline) reduced the ability to establish causal relationships, and generalization. Future research should involve a larger sample size, involve multiple settings, and take a longitudinal approach to enhance the robustness of the conclusions drawn.

CRediT authorship contribution statement

Cyrus Muriithi: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing. **Caroline Mwongera:** Conceptualization, Methodology, Resources, Supervision, Writing – review & editing. **Wuletawu Abera:** Conceptualization, Supervision, Validation, Writing – review & editing. **Christine G.K. Chege:** Validation, Writing – review & editing. **Issa Ouedraogo:** Conceptualization, Project administration, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This paper is part of the AVENIR project's activities (Adaptation and Valorization of Entrepreneurship in Irrigated Agriculture) in Tambacounda and Sedhiou Regions of Senegal, funded by Global Affairs Canada (GAC), Project No. P005390 and implemented by International Center for Tropical Agriculture (CIAT) in collaboration with Mennonite Economic Development Associates (MEDA). We thank Katiana Bougouma, Derek Linzey and Courtney Jallo (Scriptoria Solutions) for the content review and copyediting of the manuscript.

Appendix

Table A1
Description of variables

Variable	Description
Elevation (meters above sea level (m asl)	Distance above sea level.
Precipitation	A proxy of the amount of rain received.
pH	Measure of the acidity or basicity of a soil.
Temperature	The degree or intensity of heat present.
Nitrogen – g/kg	Nutrient element responsible for increase of root growth and foraging capacity for phosphorus.
Texture	The proportion of sand-, silt-, and clay-sized particles that make up the mineral fraction of the soil.
Sand	It consists of small particles of weathered rock. Sandy soils are one of the poorest types of soil for growing plants because they have very low nutrients and poor water-holding capacity, making it hard for the plant's roots to absorb water. This type of soil is very good for the drainage system. Sandy soil is usually formed by the breakdown or fragmentation of rocks like granite, limestone, and quartz.

(continued on next page)

Table A1 (*continued*)

Variable	Description
Silt	Silt has smaller particles than sandy soil and consists of rock and other mineral particles smaller than sand and larger than clay. Its smooth and fine soil quality holds water better than sand.
Cation Exchange Capacity (CEC-cmolc/kg)	Used to describe the holding capacity of a particular soil for positively charged elements (cations). It is a key determinant of soil fertility. The more the CEC in the soil, the more the ability to hold more cations, making it sufficient in calcium, magnesium etc. So. More fertility.
Bulk density (bd)	Bulk density. Dry weight of the soil divided by its volume. Dry weight will be soil particles and the air in between the particles. It is used to indicate soil compaction. High bulk density is an indicator of low soil porosity and soil compaction. High bulk density impacts available water capacity, root growth, and air and water movement through soil. Compaction increases bulk density and reduces crop yields and vegetative cover available to protect soil from erosion.
Agricultural income (annual)	Total agricultural income.
Other incomes (no agricultural) (annual)	Total income from other sources.
Remittance income (annual)	Total income from migration and remittances.
Food consumption score (FCS)	A composite score of household dietary diversity, frequency of food group consumption, and relative nutritional importance of food groups consumed by the household in the past seven days (categories: poor, borderline, acceptable).
Food expenditure share (FES)	Proportion of household expenditure used for food as compared to the total food and non-food expenditure (categories: low, moderate, high, very high).
Household dietary diversity score (HDDS)	Food groups consumed by the household using 12 food groups (count).
Household food insecurity access scale (HFIAS)	Index of the severity of food insecurity, using a standard set of nine questions to represent increasing levels of severity over a period of seven days (score from 0 to 27—the higher the score, the more food insecurity the household experienced).
Agricultural practices	Agricultural practices.
Number of social groups	Total number of social groups.
Total household members	Total household members
Total land area	Total land area
Total men hired	Total men hired
Total women hired	Total women hired
Land	Number of plots owned or leased
Crops	Number of irrigated crops
Hours	Total hours worked on a farm by household per year
Erosion	Experience in soil erosion
Irrigation method	Irrigation method applied

Table A2
Capital description variable and test

Capital	Variables	Cronbach's alpha	Kaiser-Meyer-Olkin factor adequacy (KMO)
Human	Gender of eligible respondent. Age of eligible respondent. Education of eligible respondent. Occupation of eligible respondent. Total household members. Number of members involved in providing tree management labor.	0.051	0.5
Social	Number of social groups The specific social groups the household engages with Has the household received any kind of formal support from the government or NGO over the past 12 months Over the last 12 months, how many times have you or a member of your household provided labor to someone else in the village who needed help? Over the last 12 months, how many times have you or a member of your household provided food to someone else in the village who needed help? Are there any government or NGO programs or activities in this village that help households when faced with a shock? In the last year, was there a time when people in the household needed health services but could not get them? Do you or does anyone else in your household personally know an elected government official? Could you ask the official to help your family or village if help was needed?	0.099	0.51
Financial	Total agricultural income. Total remittance income. Income for other sources. Wealth index. Has a bank. Use mobile phones for financial transactions. Regularly save cash.	0.667	0.51

(*continued on next page*)

Table A2 (*continued*)

Capital	Variables	Cronbach's alpha	Kaiser-Meyer-Olkin factor adequacy (KMO)
Natural	Number of tree varieties grown. Number of crop varieties grown. Total land area. Number of pieces of land owned. Biophysical factors (texture, elevation, ph, cec, nitrogen, temperature, precipitation, clay, silt, bd).	0.247	0.56
Physical	Total livestock owned. Total domestic items owned. Total transport items owned. Total farm assets items owned.	0.526	0.52
		α ≥ .9 Excellent .9>α > .8 Good .8 >α > .7 Acceptable .7>a≥.6 Questionable .6 > α ≥ .5 Poor .5> α Unacceptable	*0 to 0.49 unacceptable* *0.50 to 0.59 miserable* *0.60 to 0.69 mediocre* *0.70 to 0.79 middling* *0.80 to 0.89 meritorious* *0.90 to 1.00 marvelous*

Table A3
Summaries of different variables. P-values indicate the likelihood that the null hypothesis (there if no difference or the difference is equal to zero) is correct given the sample data.

Clusters		1	2	3	4	pvalue
N		300	199	120	205	
Department (%)	Sedhiou	107(35.7)	55(27.6)	21(17.5)	2(1.0)	<0.001
	Bounkiling	40(13.3)	11(5.5)	6(5.0)	14(6.8)	
	Goudomp	64(21.3)	44(22.1)	3(2.5)	0(0.0)	
	Bakel	6(2.0)	18(9.0)	69(57.5)	13(6.3)	
	Koumpentoum	10(3.3)	18(9.0)	4(3.3)	89(43.4)	
	Goudiry	8(2.7)	31(15.6)	8(6.7)	58(28.3)	
	Tambacounda	65(21.7)	22(11.1)	9(7.5)	29(14.1)	
TotalHHMembers (mean (SD))		11.43(8.28)	13.56(8.56)	8.43(7.92)	8.33(6.94)	<0.001
Resp_Gender (%)	Male	60(20.0)	32(16.1)	21(17.5)	36(17.6)	0.718
	Female	240(80.0)	167(83.9)	99(82.5)	169(82.4)	
Resp_Age (mean (SD))		39.05(11.52)	38.34(11.80)	39.81(11.56)	39.90(12.22)	0.539
AgeGroup (%)	18–34	115(38.3)	80(40.2)	47(39.2)	70(34.3)	0.644
	35+ years	185(61.7)	119(59.8)	73(60.8)	134(65.7)	
Resp_Marital (%)	Divorced	3(1.0)	1(0.5)	2(1.7)	1(0.5)	0.453
	Married monogamous	160(53.3)	115(57.8)	66(55.0)	102(49.8)	
	Married polygamous	79(26.3)	39(19.6)	27(22.5)	63(30.7)	
	Never married	31(10.3)	22(11.1)	13(10.8)	21(10.2)	
	Partnered	0(0.0)	2(1.0)	0(0.0)	0(0.0)	
	Widow or widower	27(9.0)	20(10.1)	12(10.0)	18(8.8)	
Resp_Education (%)	No formal schooling	227 (75.7)	144(72.4)	91(75.8)	175(85.4)	0.017
	Some/Still Primary	36(12.0)	19(9.5)	14(11.7)	8(3.9)	
	Completed Primary	10(3.3)	13(6.5)	4(3.3)	7(3.4)	
	Some/still secondary	1(0.3)	0(0.0)	0(0.0)	0(0.0)	
	Completed Secondary	11(3.7)	11(5.5)	7(5.8)	2(1.0)	
	Some/still college	6 (2.0)	5(2.5)	0(0.0)	2(1.0)	
	Completed college	6(2.0)	5(2.5)	0(0.0)	7(3.4)	
	Vocational School	1(0.3)	2(1.0)	2(1.7)	4(2.0)	
	Some/still University	2(0.7)	0(0.0)	1(0.8)	0(0.0)	
	Completed university	0(0.0)	0(0.0)	1(0.8)	0(0.0)	
Resp_Occupation (%)	None	2(0.7)	2(1.0)	4(3.3)	2(1.0)	<0.001
	Farming (crop only)	179(59.7)	77(38.7)	77(64.2)	125(61.0)	
	Farming (crop + livestock)	82(27.3)	99(49.7)	29(24.2)	66(32.2)	
	Casual laborer on-farm	0(0.0)	0(0.0)	0(0.0)	2(1.0)	
	Casual laborer off-farm	1(0.3)	1(0.5)	0(0.0)	0(0.0)	
	Commerce	14(4.7)	3(1.5)	1(0.8)	2(1.0)	
	Handcraft/weaving/basket	1(0.3)	2(1.0)	1(0.8)	0(0.0)	
	Herding	0(0.0)	1(0.5)	0(0.0)	0(0.0)	
	Household chores	11(3.7)	6(3.0)	5(4.2)	3(1.5)	
	Self-employed off-farm	2(0.7)	1(0.5)	0(0.0)	2(1.0)	
	Salaried employment	2(0.7)	3(1.5)	0(0.0)	0(0.0)	
	School/college child	4(1.3)	4(2.0)	2(1.7)	3(1.5)	
	Other occupation	2(0.7)	0(0.0)	1(0.8)	0(0.0)	

(*continued on next page*)

Table A3 (*continued*)

Clusters		1	2	3	4	pvalue
Household Type (%)	Male headed	172(57.3)	94(47.2)	53(44.2)	182(88.8)	<0.001
	Female-headed	36(12.0)	21(10.6)	10(8.3)	9(4.4)	
	Joint	92(30.7)	84(42.2)	57(47.5)	14(6.8)	
wealth_index_quintile (%)	Low	219(73.0)	148(74.4)	45(37.5)	168(82.0)	<0.001
	Middle	76(25.3)	45(22.6)	46(38.3)	31(15.1)	
	High	5(1.7)	6(3.0)	29(24.2)	6(2.9)	
Wealth index (mean (SD))		−0.12(1.66)	−0.01(1.67)	2.10(2.65)	−0.54(1.84)	<0.001
FoodCS (mean (SD))		12.93(7.28)	9.77(7.36)	9.78(7.66)	4.66(4.46)	<0.001
FoodCS Category (%)	Poor	252(84.0)	183(92.0)	109(90.8)	203(99.0)	<0.001
	Borderline	46(15.3)	16(8.0)	10(8.3)	2(1.0)	
	Acceptable	2(0.7)	0(0.0)	1(0.8)	0(0.0)	
FESCategory (%)	Low FES	193(68.7)	120(75.9)	60(53.6)	75(47.8)	<0.001
	Moderate FES	49(17.4)	15(9.5)	20(17.9)	48(30.6)	
	High FES	22(7.8)	11(7.0)	11(9.8)	23(14.6)	
	Very high FES	17(6.0)	12(7.6)	21(18.8)	11(7.0)	
FoodExpShare (mean (SD))		38.11(22.45)	29.52(24.54)	42.24(29.33)	36.74(27.69)	<0.001
HDDS (mean (SD))		5.90(2.82)	4.66(2.77)	4.11(2.94)	2.47(1.97)	<0.001
HFIAS (mean (SD))		3.93(4.38)	4.30(5.13)	3.98(4.83)	7.53(5.80)	<0.001
numSG (mean (SD))		0.67(0.66)	0.51(0.59)	0.65(0.66)	0.36(0.50)	<0.001
NumIrriCrops (mean (SD))		1.16(1.25)	2.34(1.10)	1.90(1.10)	0.22(0.56)	<0.001
NumCSAs (mean (SD))		1.36(0.82)	1.50(0.76)	1.62(1.00)	1.33(0.72)	0.004
AgriInc (mean (SD))		143108.28 (207765.44)	170286.60 (246493.52)	224413.04 (292335.57)	60063.52 (124850.60)	<0.001
OtherIncomes (mean (SD))		757507.11 (751071.09)	737170.54 (844934.85)	1434134.20 (1523567.13)	519080.86 (640065.26)	<0.001
RemitIncome (mean (SD))		67051.33 (196680.19)	75756.09 (225567.60)	173033.43 (537959.09)	11617.59 (55177.24)	<0.001
precip (mean (SD))		392.44 (291.93)	526.16 (389.85)	911.23(494.72)	913.35 (226.08)	<0.001
clay (mean (SD))		13.78(4.64)	15.01(5.79)	19.31(6.83)	18.42(4.32)	<0.001
oc (mean (SD))		6.86(4.16)	9.30(6.39)	16.13(9.67)	13.84(4.84)	<0.001
silt (mean (SD))		10.08(2.66)	9.70(2.63)	9.51(3.32)	8.56(1.90)	<0.001
sand (mean (SD))		76.09(6.27)	75.09(7.21)	67.78(14.60)	73.06(5.41)	<0.001
temp (mean (SD))		24.18(1.48)	23.43(2.10)	20.73(4.59)	21.05(1.84)	<0.001
nitrogen (mean (SD))		0.53(0.21)	0.59(0.26)	0.81(0.39)	0.79(0.23)	<0.001
cec (mean (SD))		10.08(2.99)	9.47(3.13)	8.91(3.29)	7.45(2.15)	<0.001
ph (mean (SD))		7.38(0.80)	7.07(0.95)	6.12(1.44)	6.09(0.50)	<0.001
texture (mean (SD))		9.21(1.38)	8.89(1.73)	7.20(2.25)	8.03(1.47)	<0.001
elevatn (mean (SD))		565.20 (267.26)	687.68 (394.68)	1037.95 (519.55)	1132.38 (357.35)	<0.001
bd (mean (SD))		1380.37 (123.33)	1340.40 (241.60)	1277.46 (301.27)	1358.37 (55.10)	<0.001
TreeMarket -walking minutes (mean (SD))		661.98 (4324.82)	800.58 (4415.93)	30.29 (28.65)	18.83 (15.84)	0.769
CropSeedSource -walking minutes (mean (SD))		40.61 (39.18)	47.28 (66.96)	64.87 (70.21)	21.00 (24.01)	0.282
ProductSalesMarket -walking minutes (mean (SD))		64.94 (136.86)	38.43 (45.11)	43.86 (38.86)	64.29 (51.74)	0.108
AgroProcessedProductSalesMarket -walking minutes (mean (SD))		55.00 (8.66)	31.44 (19.11)	Na (NA)	120.00 (84.85)	0.011
TotalHarvest(KG) (mean (SD))		522.38 (641.79)	488.57 (516.80)	1710.96 (2428.04)	219.16 (364.47)	<0.001
TotalMarketed(KG) (mean (SD))		198.31 (310.63)	180.27 (259.03)	1478.39 (2230.30)	214.38 (316.09)	<0.001
Organic (manure, compost) (mean (SD))		389.86 (577.58)	859.35 (3476.26)	1152.64 (1351.32)	290.00 (266.41)	0.474
Inorganic (mean (SD))		101.35 (110.01)	65.34 (68.06)	157.49 (246.73)	79.78 (72.31)	0.003
Both (Organic and Inorganic) (mean (SD))		100.25 (70.48)	152.00 (160.49)	1251.25 (1677.64)	350.00 (353.55)	0.176
Social group (%)	Agricultural marketing/ commercialization (including livestock/ fisheries)	11 (5.4)	3 (2.9)	10 (12.8)	3 (4.1)	<0.001
	Agricultural producers' group (Including/livestock/ fisheries)	74 (36.6)	46 (45.1)	34 (43.6)	32 (43.8)	
	charitable group (helping others)	11 (5.4)	5 (4.9)	1 (1.3)	0 (0.0)	

(*continued on next page*)

Table A3 (*continued*)

Clusters		1	2	3	4	pvalue
	Civic groups (improving community)	11 (5.4)	3 (2.9)	3 (3.8)	0 (0.0)	
	Environment/climate management group	0 (0.0)	0 (0.0)	1 (1.3)	1 (1.4)	
	Food security and nutrition	2 (1.0)	0 (0.0)	0 (0.0)	0 (0.0)	
	Irrigation water use association (IWUA)	1 (0.5)	0 (0.0)	5 (6.4)	1 (1.4)	
	Local government	0 (0.0)	0 (0.0)	1 (1.3)	1 (1.4)	
	Mutual help or insurance group (including burial societies)	1 (0.5)	1 (1.0)	2 (2.6)	0 (0.0)	
	Other group (only if it does not fit into one of the other categories)	31 (15.3)	3 (2.9)	7 (9.0)	6 (8.2)	
	Religious group	26 (12.9)	29 (28.4)	5 (6.4)	12 (16.4)	
	Savings and credit group (including SACCOs/merry-go-rounds/VSLAs)	28 (13.9)	9 (8.8)	1 (1.3)	14 (19.2)	
	Water users' group	6 (3.0)	3 (2.9)	8 (10.3)	3 (4.1)	
Access to the village (%)	Paved road (e.g., asphalt)	16 (5.3)	12 (6.0)	11 (9.2)	5 (2.4)	$<$0.001
	Dirt or gravel road	138 (46.0)	106 (53.3)	78 (65.0)	121 (59.0)	
	Mixed paved and dirt	1 (0.3)	7 (3.5)	3 (2.5)	3 (1.5)	
	Footpath/trail	57 (19.0)	32 (16.1)	15 (12.5)	58 (28.3)	
	Don't know	2 (0.7)	12 (6.0)	0 (0.0)	1 (0.5)	
	Refused	1 (0.3)	0 (0.0)	0 (0.0)	0 (0.0)	
	Other	85 (28.3)	30 (15.1)	13 (10.8)	17 (8.3)	

References

[1] B. Lenaerts, B.C.Y. Collard, M. Demont, Review: improving global food security through accelerated plant breeding, Plant Sci. 287 (2019), https://doi.org/10.1016/j.plantsci.2019.110207.

[2] C. Mwongera, K.M. Shikuku, J. Twyman, P. Läderach, E. Ampaire, P. Van Asten, S. Twomlow, L.A. Winowiecki, Climate smart agriculture rapid appraisal (CSA-RA): a tool for prioritizing context-specific climate smart agriculture technologies, Agric. Syst. 151 (2017), https://doi.org/10.1016/j.agsy.2016.05.009.

[3] R. Frelat, S. Lopez-Ridaura, K.E. Giller, M. Herrero, S. Douxchamps, A.A. Djurfeldt, O. Erenstein, B. Henderson, M. Kassie, B.K. Paul, C. Rigolot, R.S. Ritzema, D. Rodriguez, P.J.A. Van Asten, M.T. Van Wijk, Drivers of household food availability in sub-Saharan Africa based on big data from small farms, Proceedings of the National Academy of Sciences of the United States of America 113 (2) (2016), https://doi.org/10.1073/pnas.1518384112.

[4] B. Haile, C. Azzarri, C. Roberts, D.J. Spielman, Targeting, bias, and expected impact of complex innovations on developing-country agriculture: evidence from Malawi, Agric. Econ. 48 (3) (2017), https://doi.org/10.1111/agec.12336.

[5] C. Mwongera, C. Lamanna, H.N. Kamau, E. Girvetz, Scaling climate-smart agriculture for agricultural transformation in Southern Africa, in: Transforming Agriculture in Southern Africa: Constraints, Technologies, Policies and Processes, 2019, https://doi.org/10.4324/9780429401701-13.

[6] A. Notenbaert, C. Pfeifer, S. Silvestri, M. Herrero, Targeting, out-scaling and prioritising climate-smart interventions in agricultural systems: lessons from applying a generic framework to the livestock sector in sub-Saharan Africa, Agric. Syst. 151 (2017), https://doi.org/10.1016/j.agsy.2016.05.017.

[7] S. Upadhaya, J.G. Arbuckle, L.A. Schulte, Developing farmer typologies to inform conservation outreach in agricultural landscapes, Land Use Pol. 101 (2021), https://doi.org/10.1016/j.landusepol.2020.105157.

[8] A. Notenbaert, M. Herrero, R. Kruska, L. You, S. Wood, P. Thornton, A. Omolo, Classifying Livestock Production Systems for Targeting Agricultural Research and Development in a Rapidly Changing World. ILRI, International Livestock REsearch Institute), Nairobi, Kenya, 2009. *Discussion Paper No. 19*.

[9] B.H. Gebrekidan, T. Heckelei, S. Rasch, Characterizing farmers and farming system in kilombero valley floodplain, Tanzania, Sustainability 12 (17) (2020), https://doi.org/10.3390/su12177114.

[10] N. Guiomar, S. Godinho, T. Pinto-Correia, M. Almeida, F. Bartolini, P. Bezák, M. Biró, H. Bjørkhaug, Bojnec, G. Brunori, M. Corazzin, M. Czekaj, S. Davidova, J. Kania, S. Kristensen, E. Marraccini, Z. Molnár, J. Niedermayr, E. O'Rourke, A. Wästfelt, Typology and distribution of small farms in Europe: towards a better picture, Land Use Pol. 75 (2018), https://doi.org/10.1016/j.landusepol.2018.04.012.

[11] I. Daloğlu, J.I. Nassauer, R.L. Riolo, D. Scavia, Development of a farmer typology of agricultural conservation behavior in the american corn belt, Agric. Syst. 129 (2014), https://doi.org/10.1016/j.agsy.2014.05.007.

[12] S. Kumar, P. Craufurd, A. Haileslassie, T. Ramilan, A. Rathore, A. Whitbread, Farm typology analysis and technology assessment: an application in an arid region of South Asia, Land Use Pol. 88 (2019), 104149, https://doi.org/10.1016/j.landusepol.2019.104149. ISSN 0264-8377.

[13] C. Le Page, W. Naivinit, G. Trébuil, N. Gajaseni, Companion modelling with rice farmers to characterise and parameterise an agent-based model on the land/water use and labour migration in Northeast Thailand, 1, in: Empirical Agent-Based Modelling - Challenges and Solutions, The Characterisation and Parameterisation of Empirical Agent-Based Models, 2014, https://doi.org/10.1007/978-1-4614-6134-0.

[14] A. Wezel, M. Casagrande, F. Celette, J.F. Vian, A. Ferrer, J. Peigné, Agroecological practices for sustainable agriculture. A review, Agron. Sustain. Dev. 34 (Issue 1) (2014), https://doi.org/10.1007/s13593-013-0180-7.

[15] B.M. Orounladji, F.O. Oke, K. Tozo, C.A.A.M. Chrysostome, Socioeconomic correlates, typology and characterization of indigenous Guinea fowl (Numida meleagris, Linnaeus) farming in Benin, West Africa, Heliyon 8 (4) (2022), https://doi.org/10.1016/j.heliyon.2022.e09226.

[16] B. Konmy, P.A. Olounladé, E.V.B. Azando, C.C. Dansou, R.K. Dahoue, S. yô Doko Allou, S.M. Hounzangbé-Adoté, L. Baba-Moussa, Typology of rabbit rearing systems in tropical areas: a case of Benin (West Africa), Heliyon 9 (4) (2023), https://doi.org/10.1016/j.heliyon.2023.e14718.

[17] S.W. Omamo, X. Diao, S. Wood, J. Chamberlin, L. You, S. Benin, U. Wood-Sichra, A. Tatwangire, Strategic Priorities for Agricultural Development in Eastern and Central Africa, vol. 150, Research Report of the International Food Policy Research Institute, 2006, https://doi.org/10.2499/9780896291584rr150.

[18] Forum for the Future, The Five Capitals Model – a Framework for Sustainability, Action for a Sustainable World, 2007.

[19] R. Chambers, G. Conway, Sustainable Rural Livelihoods: Practical Concepts for the 21st Century, IDS Discussion Paper 296, Institute of Development Studies, Brighton, 1992.

[20] A. Bebbington, Capitals and capabilities: a framework for analyzing peasant viability, rural livelihoods and poverty, World Dev. 27 (12) (1999), https://doi.org/10.1016/S0305-750X(99)00104-7.

[21] J. Sayer, B. Campbell, The science of sustainable development: local livelihoods and the global environment, in: The Science of Sustainable Development: Local Livelihoods and the Global Environment, 2004.

[22] E. Fiorillo, E. Di Giuseppe, G. Fontanelli, F. Maselli, Lowland rice mapping in Sédhiou region (Senegal) using sentinel 1 and sentinel 2 data and random forest, Rem. Sens. 12 (20) (2020) 1–23, https://doi.org/10.3390/rs12203403.

[23] I. Rgphae, M.F. Mbengue, C.T. Ndiaye, O. Sarr, E. Hadji, M. Gueye, E. De Redaction, Rapport Définitif RGPHAE 2013 | EQUIPE DE DIRECTION EQUIPE DE DIRECTION, 2013. http://anads.ansd.sn/index.php/catalog/?page=1&ps=15.

[24] W.C. Cochran, Snedecor G W & Cochran W G. Statistical Methods Applied to Experiments in Agriculture and Biology, 1956, in: Citation Classics, Iowa State University Press, Ames, Iowa, 1977. Vol. 19, Issue 19.

[25] S. Randall, E. Coast, P. Antoine, N. Compaore, F.B. Dial, A. Fanghanel, S.B. Gning, B.G. Thiombiano, V. Golaz, S.O. Wandera, UN census "households" and local interpretations in africa since independence, Sage Open 5 (2) (2015), https://doi.org/10.1177/2158244015589353.

[26] J.L. Leroy, M. Ruel, E.A. Frongillo, J. Harris, T.J. Ballard, Measuring the food access dimension of food security: a critical review and mapping of indicators A critical review and mapping of indicators. Food and Nutrition Bulletin, Food Nutr. Bull. 36 (2) (2015) 167–195, 36(2).

[27] L. Kaufman, P.J. Rousseeuw, Finding groups in data: an introduction to cluster analysis (wiley series in probability and Statistics), in: Eepe.Ethz.Ch, vol. 66, 1990.

[28] L. Kaufman, P.J. Rousseeuw, Partitioning around medoids (program PAM), in: Finding Groups in Data: an Introduction to Cluster Analysis, Wiley, Hoboken, 2008.

[29] J. Pages, Analyse factorielle de données mixtes, Rev. Stat. Appl. 52 (4) (2004).

[30] A. Kassambara, F. Mundt, factoextra, in: R Package, 2017, 1.0.5.

[31] J.F. Hair, W.C. Black, B.J. Babin, R.E. Anderson, Multivariate Data Analysis, Analysis, 2006.

[32] S. Datta, S. Datta, Comparisons and validation of statistical clustering techniques for microarray gene expression data, Bioinformatics 19 (4) (2003), https://doi.org/10.1093/bioinformatics/btg025.

[33] ScienceDirect Topics, Probit Analysis - an Overview, Encyclopedia of Applied Plant Sciences, 2003. www.sciencedirect.com/topics/agricultural-and-biological-sciences/probit-analysis.

[34] J. Lax, J. Krug, Livelihood Assessment: a participatory tool for natural resource dependent communities, Thunen 7 (2013).

[35] R. Nyairo, T. Machimura, T. Matsui, A combined analysis of sociological and farm management factors affecting household livelihood vulnerability to climate change in rural Burundi, Sustainability 12 (10) (2020), https://doi.org/10.3390/su12104296.

[36] T. Li, H. Zhang, C. Yuan, Z. Liu, C. Fan, A PCA-based method for construction of composite sustainability indicators, Int. J. Life Cycle Assess. 17 (5) (2012), https://doi.org/10.1007/s11367-012-0394-y.

[37] B. Paudel, R.C. Khanal, K. Bhatta, P. Chaudhary, Climate-smart agriculture in Nepal, CSA Country Profiles for Asia Series 1 (1) (2017) 1–10. https://hdl.handle.net/10568/83339.

[38] M. Tavakol, R. Dennick, Making sense of Cronbach's alpha, Int. J. Med. Educ. 2 (2011), https://doi.org/10.5116/ijme.4dfb.8dfd.

[39] D.G. Altman, J.M. Bland, Statistics Notes: Cronbach's Alpha, BMJ, 1996, p. 314.

[40] R.F. Devellis, Scale Development: Theory and Aplications, 2003.

[41] J. Nunnally, I. Bernstein, Psychometric Theory, McGraw-Hill, New York, 1994, p. 3, 1994.

[42] D.L. Streiner, Starting at the beginning: an introduction to coefficient alpha and internal consistency, J. Pers. Assess. 80 (1) (2003), https://doi.org/10.1207/S15327752JPA8001_18.

[43] C.D. Dziuban, E.C. Shirkey, When is a correlation matrix appropriate for factor analysis? Some decision rules, Psychol. Bull. 81 (6) (1974), https://doi.org/10.1037/h0036316.

[44] M. Abdul-Razak, S. Kruse, The adaptive capacity of smallholder farmers to climate change in the Northern Region of Ghana, Climate Risk Management 17 (2017) 104–122, https://doi.org/10.1016/j.crm.2017.06.001.

[45] L. Kabobah, D. Nukpezah, Y. Ntiamoa-Baidu, Adaptive capacity of farmers to climate change in the Kassena Nankana municipality of Ghana: implications for climate adaptation strategies, West African Journal of Applied Ecology 26 (2018) 14–26.

[46] M. Herrero, A. Notenbaert, P. Thornton, C. Pfeifer, S. Silvestri, A. Omolo, C. Quiros, A Framework for Targeting and Scaling-Out Interventions in Agricultural Systems, CCAFS Working Paper, 2014, p. 62.

[47] FAO, Climate-smart agriculture sourcebook. Food and agriculture organization of the united nations, in: Sourcebook on Climate-Smart Agriculture, Forestry and Fisheries, 2013.