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Do Community Capitals Influence Climate Adaptation? Critique of Financial, Physical, Human and Social Capital in the Adoption of Climate Smart Agriculture Technologies among Smallholder Farming Community in Lamu County, Kenya

Walter Jabali Jilani[1*], Prof. Annie Hilda Ong'ayo[2] & Dr. Andrew W. Wamukota[3]

[1*]PhD Student, School of Environmental and Earth Sciences, Pwani University

[2]Lecturer, School of Environmental and Earth Sciences, Pwani University

[3]Lecturer, School of Environmental and Earth Sciences, Pwani University

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Abstract

Purpose: This study aimed to establish a framework for testing the community capitals theory and assessing the empirical significance of financial, physical, human, and social capital in the adoption of climate-smart agriculture technologies.

Materials and Methods: Data was collected through semi-structured questionnaires administered to 256 randomly selected household heads. An ordinal logistic regression model was employed to analyze the significance of community capitals in climate-smart agriculture adoption. The data is presented in tables.

Findings: The results revealed several important findings. Access to finance has a significant positive association with Climate-Smart Agriculture adoption (P<0.001, OR=3.23). Input subsidies are also significantly positively associated with Climate-Smart Agriculture adoption (P=0.001, OR=3.66). Training shows a significant positive association with Climate-Smart Agriculture adoption (P<0.007, OR=2.03). Labor has a highly significant and positive relationship with Climate-Smart Agriculture adoption (P=0.001, OR=8.97). Interaction positively and significantly correlates with higher levels of Climate-Smart Agriculture adoption (P=0.021, OR=4.04). Additionally, empowerment demonstrates a significant positive association with Climate-Smart Agriculture adoption (P=0.006, OR=2.96). Notably, the model challenged the conventional view of finance and labor as independent determinants for climate-smart agriculture adoption, instead positioning them within a social context.

Implications to Theory, Practice and Policy: The study suggests that climate action programs should prioritize social ties over investments in financial, physical, or human interventions to enhance climate-smart agriculture adoption and promote resilience. Lastly, combining the Community Capital Framework with Social Capital Theory offers a more detailed understanding of the factors influencing Climate-Smart Agriculture adoption, emphasizing the interaction between various types of capital and social dynamics.

Keywords: *Financial, Physical, Human, Social Capital, Climate-Smart Agriculture Technologies*

1.0 INTRODUCTION

Approximately, 75% of the world's rural population, depends in/directly on agriculture for their livelihoods (FAO, 2017). However, above or below-normal rainfall regimes due to climate change threaten the capabilities of these populations realize food and income security. This is more pronounced among smallholder farmers in Africa (Komarek et al., 2018). Climate-Smart Agriculture (CSA) is being promoted as a viable option for climate change mitigation. This wide range of technologies addresses the negative impacts by improving system resilience, lowering greenhouse gas emissions and increasing production (FAO, 2014). The use of community capital to explain adoption of CSA has been exemplified in many studies(Akrofi-Atitianti et al., 2018; Jayne et al., 2018; Komarek et al., 2018). For instance, a study in Ghana, (Collins-Sowah et al., 2019) found evidence of pineapple farmers altering their inputs to match those of their neighbors who had previously succeeded after implementing CSA technology. (Balew et al., 2014) acknowledges the role of farmers' horizontal transmission channels in Ethiopia's Central regions, where friends or neighbors swap seeds, agricultural inputs, and information, saving them money they may otherwise spend on purchases. In Teso, Kenya, farmers who received credit during a farming season were more likely to use it to adopt more of the CSA practices than those who did not receive (Wekesa et al., 2018).

In Lamu County, the Kenya Climate Smart Agriculture Project (KCSAP) has provided training for smallholders through farmers' groups focusing on the cashew nut, dairy, cotton, and poultry value chains. Additionally, smallholders have benefited from input subsidies provided by the County government and other development partners. These initiatives have revitalized the agricultural sector in Lamu, which is adversely affected by climate variability and risks being overshadowed by fishing and tourism activities. However, despite these efforts, the technologies adopted have not been assessed in a way that demonstrates their effectiveness. As a result, the choice of CSA currently serves as a survival technique rather than a resilience mechanism. Evaluation at the governance levels will uncover the specific barriers faced by the community, enabling the design of tailored interventions to address these challenges, and promoting broader and more effective adoption of CSA technologies.

Problem Statement

There is a growing shift from conventional agriculture, which generates greenhouse gases, towards conservation agriculture due to its numerous benefits. CSA encompasses agricultural practices that sustainably boost productivity, adaptation and mitigation. A crucial component of CSA is conservation agriculture, which focuses on minimal soil disturbance, maintaining soil cover, and using improved crop breeds. These practices reduce the reliance on excessive chemicals, thereby enhancing soil health and promoting environmental sustainability while also providing economic benefits for farmers. In Lamu County, a CSA program is being implemented to enhance household resilience. However, the actual adoption of CSA practices largely depends on the decisions and capabilities of individual farmers. This challenge is further complicated by the lack of clarity regarding the financial, human, physical, and social capital that influence farmers' decision-making processes. Additionally, there is a need to identify the predominant forms of investments in assets, operations, and risk specific to Lamu County. This ambiguity undermines the understanding of the factors that explain and mitigate the unreliability and devaluation of CSA practices. This study aims to improve the understanding of CSA adoption by identifying the specific elements that contribute to its acceptance as a socially and economically viable option.

Theoretical Framework

This study adopts the Community Capital Framework (CCF) by (Flora & Emery, 2006) and the Social Capital Theory. The CCF is prominent as both a policy and program guideline amongst development agencies in designing climate actions in rural communities. Broadly, it argues that by possessing a stock of capital, individuals and communities demonstrate commitment, resources and skills to address problems, opportunities and likely become resilient (Pigg et al., 2013). With regards to climate change, the CCF is borrowed heavily by the United Nations Climate Change Secretariat in the form of nationally-determined contributions (NDCs) that argue in favor of building financial, technological and enforcement capacities of parties (IISD, 2014). However, the convention appreciates the complexity regarding the sources, funds, processes and initiatives by which vulnerable countries should acquire or utilize these capitals including utilizing capitals outside the UNFCCC(IISD, 2014). Owing to the gravity of climate change as an existential threat and the severity of accountability measures proposed under UNFCCC it behooves researchers in this field to demonstrate the empirical significance of these capitals to climate adaptation.

Fortunately, the UNFCCC has already acknowledged the variations in socioeconomic capitals across and within parties, a fact that could demonstrate how variations a community's capital portfolio could also vary in its losses and responses to climate change(Fey et al., 2006) . This is possible because in the CCF, each capital exists as a unique subsystem within a larger system (Flora & Emery, 2006). In light of this argument, (Fey et al., 2006) used a three-tiered ranking system (High, Medium and Low) as a way of categorizing different groups in the community who have successfully, undertaken a development initiative. This provoked the argument whether all or a particular form of capital were responsible for realizing adaptation and whether the argument could squarely rest on CCF or others such as the Social Capital Theory. The Social Capital Theory explores the social dimensions of the community through bonding and bridging. Integrating the CCF with Social Capital Theory can offer a more detailed and comprehensive understanding of the factors influencing CSA adoption. This combined approach can help develop more effective, multifaceted strategies for CSA adoption by addressing both the social dynamics and the broader resource base of communities.

Preliminary observations indicate that smallholder farmers in Lamu County, having benefited from KSCAP training, have gained the knowledge and skills necessary to adopt CSA technologies. These are essential aspects of human capital. However, other factors of human capital, such as labor, depend entirely on the smallholders' financial empowerment and their ability to mobilize labor through community networking. Likewise, although there are subsidy programs to help acquire farm inputs, farmers still struggle to obtain sufficient inputs, particularly those that need to be purchased, borrowed, or leased from others. For this reason, the researchers sought to examine the exact nature, source and utilization of each community capital and test its association to social order or the capital. This way, it would be possible to advice climate action managers with more precision.

Another challenge emerged given that 87% of UNFCCC parties lacked data and uniform metrics for assessing important community capitals. The discrepancies are complicated further given the lack of uniformity in academia at not only measuring community capitals but climate adaptation as well (Azumah, 2020; Raquel et al., 2023). On the other hand, social capital theory focuses solely on social relationships, thereby may overlook other critical factors like economic resources or environmental conditions that also influence climate adaptation and CSA adoption (Han et al., 2022). This study attempts to address the gaps by providing a unified methodology for quantifying community capital and adaptation.

2.0 MATERIALS AND METHODS

Study Area

The study area is Lamu County, found on the North coast of Kenya. The County lies between latitudes 1° 40" and 20° 30" South and longitudes 40° 15" and 40° 38" East. Lamu County has two sub-counties, namely, Lamu West and Lamu East. Agriculture is a crucial sector in Lamu West sub-County, contributing 90 percent of the total household incomes (County Government of Lamu, 2018). In Lamu East sub-County, most residents are fishers, with some supplementing it with farming (County Government of Lamu, 2018). The County is vulnerable to drought and heat stress and this results in adverse conditions for agricultural production (Yvonne et al., 2020).

Research design

A descriptive survey research design was used in the investigation. The design was used to characterize the qualities of the person, subject, phenomena, or condition under investigation in its natural environment (Sarwono, 2022). In this study, the design was useful because it allowed for the collection of both qualitative and quantitative data from purposively and randomly selected respondents utilizing a semi-structured questionnaire (Sarwono, 2022).

Target Population and Sample Size Determination

The research targeted 710 smallholder households in Lamu County who were trained on CSA from 2017 to 2021 by KCSAP. Out of a total of 710 households, 256 were chosen at random, proportionate to the size of the population in each value chain, based on the sampling size. The Stat Trek Random-Number Generator was used to generate random numbers for the households in each value chain, which were then used to choose samples from the whole set of household data. The KCSAP office in Lamu County provided a list of the names of the households that received training on four value chains. The sample size of 256 smallholder households was calculated based on (Yamane, 1967) formula sample sizes determination.

$$n = \frac{N}{1 + N(e)^2}$$

Where; n is the sample size,

N is the population size,

1 is the probability of the event occurring,

e is the level of precision (0.05)

95% confidence level.

Using the above formula a computation for the sample size of the smallholder households

$$n = \frac{710}{1+710(0.05)^2} \quad n = 710 \quad \frac{n = 710}{1+710(0.0025)} \quad \frac{}{2.775} \quad n=255.9$$

Data Collection Tool and Reliability

A semi-structured questionnaires were administered to selected smallholder households in Lamu County. Reliability test was done during a pilot test. Test re-test method was used to test reliability of the questionnaire (Sarwono, 2022). The questionnaires were administered to a group of respondents selected for the pilot test. The researcher then re-administered the questionnaire to the same group of participants after 7 days. This method is relatively simple to execute and is best for assessing stable characteristics of individuals such as anxiety. Validity of the instruments was determined before being used for data collection in the field by supervisors. This was done to assess the validity of the instrument to avoid biased responses from the respondents. This process also ensured measuring instruments are valid and resulted in correct measurement (Sarwono, 2022).

Table 1: Reliability Statistics

Reliability Statistics		
Questions	**Cronbach's Alpha**	**Number of Questions**
1. Perceptions on accessibility of finances	.882	5
2. Accessibility of physical capital	.742	3
3. Input subsidies	.796	2
4. Effectiveness of training	.895	2
5. Labor	.713	2
6. Empowerment	.868	4
7. Interaction	.858	5
8. Trust	.861	5

The questionnaire was tested for reliability and validity to ensure accurate data collection. To establish internal consistency, Cronbach's alpha was calculated for each latent variable. Based on established social science standards, an observed value of 0.70 or above should be considered acceptable (Lamm et al., 2020). In comparison to the literature, the Cronbach's Alpha of all set of questions on a variable was above 0.70 and a response rate of 82.3 were typically satisfactory. The study variables were analyzed using qualitative and quantitative data analysis approaches using statistical software r version 4.3.2.

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Operationalization and Measurement of Variables

The dependent variable (Adoption of CSA technology) was measured using the adoption quotient (Sengupta, 1967)formula score for an individual smallholder was generated given by.

The formula reads:

$$\text{Adoption Quotient} = \frac{\text{Total number of CSA tchnologies adopted by farmer}}{\text{Maximum number of CSA adopted in a Value chain}} * 100$$

An Adoption Quotient score was generated by ranking the number of CSA technologies that the smallholders had adopted into three outcome categories: high, medium and low 1) Low Adopters (scores between 1 and 39). Smallholders under this group have relatively low adoption levels, adopting a limited number of CSA technologies. 2) Medium Adopters (scores between 40 and 59). Smallholders under this group have adopted a substantial number of CSA technologies, indicating a more significant engagement with a variety of CSA technologies. 3) High Adopters (scores of 60 and above). These smallholders have incorporated a broad range of CSA technologies into their farms, potentially serving as examples of successful and sustainable adoption. The Adoption Quotient scores offer a structured and systematic way to categorize smallholders based on their level of adoption of CSA technologies, facilitating targeted strategies for promoting sustainable agricultural technologies (Sengupta, 1967).

Table 2: Measuring Adoption of Independent Variables

Financial capital	
Variable	**How it is measured**
Financial	**Likert scale** on statements on determining to what extent do you; Strongly Disagree=1, Disagree=2, Neutral=3, Agree=4, Strongly Agree=5
Physical capital	
Variable	**How it is measured**
Input sources	**Likert scale** on statements to what extent do you; Strongly Disagree=1, Disagree=2, Neutral=3, Agree=4, Strongly Agree=5
Distance to the inputs	Measured in kilometres
Subsidies	**Likert scale** on statements to what extent do you; Strongly Disagree=1, Disagree=2, Neutral=3, Agree=4, Strongly Agree=5

Human capital	
Variable	**How it is measured**
Education level	The highest level of education attained by the respondent; Tertiary=4, Secondary=3, Primary=2, Madrassa=1, None=0
Training	**Composite score** obtained by farmer based frequent attendance in training (once, twice, thrice….) **Likert scale** on statements to what extent do you; Strongly Disagree=1, Disagree=2, Neutral=3, Agree=4, Strongly Agree=5
Labour	**Likert scale** on statements to what extent do you; Strongly Disagree=1, Disagree=2, Neutral=3, Agree=4, Strongly Agree=5

Social capital	
Variable	**How it is measured**
Group involvement	**Dummy variable**; Belong to member of farmers group/cooperative (Yes= 1No= 0)
Empowerment	**Likert scale** on statements to what extent do you; Strongly Disagree=1, Disagree=2, Neutral=3, Agree=4, Strongly Agree=5
Networking	**Dummy variable**;1 0 if not selected
Interaction	**Likert scale** on statements to what extent do you; Very often=3, Often=2, Rarely=1.
Trust	**Likert scale** on statements to what extent do you; Strongly Disagree=1, Disagree=2, Neutral=3, Agree=4, Strongly Agree=5

Model Specification

The ordinal logistic regression model equation is expressed as

$P(Yi > j) \ = g(X\beta j) \ = \frac{exp(\alpha j + Xi\beta j)}{2!}, j = 1,2 \dots, M-1$.......................... (1)

Where M is the number of categories of the ordinal regression. From equation 1, the probabilities that Y will take on each of the values 1,…,*M* are equal to

$P(Yi = 1) \ = 1 - g(Xi\beta j)$ .... (2)

$P(Yi = j) \ = g(Xi\beta j - 1) \ - g(Xi\beta j) \ \ j = 2, \dots, M - 1P(Yi = M) \ = g(Xi\beta M - 1)$ ..(3)

$Yi = \beta 0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots \beta_n X_n + \mu i$...................................... (4)

The dependent variable Yi=level of CSA technologies (high adopters= 3; medium adopters= 2; Low adopters=1). $X_1 \dots X_n$ represents the independent variables; $\beta_1 \dots \beta_n$ represent the parameters of the independent variable; and β_0 represents the intercept, while μi represents the error term

as.factor (CSA adoption Level) ~ Finance access β_1+ Inputs access β_2 + Input subsidiesβ_3+Distanceβ_4+ Educationβ_5+ Perceptions effective Trainingβ_6+ Perceptions on Labor strategyβ_7 + Number of times Trainedβ_8+ as.factor (Networking) β_9 +as.factor (Technology adoption) β_{10} +as.factor (Business Skills) β_{11} + as.factor(Marketing) β_{12} + Trustβ_{13} + Interactionβ_{14} + Empowermentβ_{15} $+ \mu i$, data=Ordinaldf, link="logit")

3.0 FINDINGS

Diagnostic Test

Before conducting ordinal logistic regression, diagnostic tests were performed. They included normality, correlation and a Brant Tests of parallel lines. These tests allowed the assumption to be tested and several types of biases to be addressed.

The final AIC (236.23) model was significantly better fit than the null model (498.29; X^2= 292.05, df= 15, *P*= 2.2e-16 ***) Nagelkerke R Square (0.7958). The regression model was significant at *P*= 2.2e-16 ***, meaning that the independent variables are indeed contributing meaningful information to explain the variability in the ordinal outcome (Nahhas, 2023).

Results in Table 3 were an output of a diagnostic test when assumed that the effect of each independent variable is the same for each change in the dependent variable. According to (Williams, 2016), the assumption of the ordinal logistic regression test holds when the p-value is greater than 0.05 i.e. not be significant. For this model we conclude that the Assumption for a Parallel Regression line holds.

Table 3: Brant Test of Parallel Lines/ Proportional Odds

Test for		**X^2**	**df**	**Probability**
Omnibus		30.13	15	0.01
Financial access		1.26	1	0.26
Inputs access		5.29	1	0.02
Input subsidies		0.58	1	0.45
Distance		0.46	1	0.5
Education		3.08	1	0.08
Effective training		0.82	1	0.37
Number of times trained		0.62	1	0.43
Labor strategy		5.94	1	0.01
as.factor(Networking) No	2.14	1	0.14	
as.factor(Tech_adoption) No	2.09	1	0.15	
as.factor(Business_skills) No	0.01	1	0.91	
as.factor(Marketing) No	3.88	1	0.05	
Trust		1.99	1	0.16
Interaction		0.78	1	0.38
Empowerment		0.31	1	0.58

H0: Parallel Regression Assumption holds

Regression Results

Table 4: Ordinal Regression Results

Variable		**OR**[1]	**95%**	**CI**[1]	***p*-value**
Access to Finance		3.23	1.66,	6.54	**0.000752 *****
Perceptions access to Inputs		1.12	0.65,	1.94	0.670
Input subsidies		3.66	2.08,	6.83	**1.69e-05 *****
Distance		1	-0.88,	1.13	0.974
Education		0.95	0.67,	1.36	0.786
Effectiveness of Training		2.03	1.23,	3.47	**0.006985 ****
Number of times Trained		1.17	0.91,	1.51	0.224
Labor		8.97	4.73,	18.7	**2.82e-10 *****
as.factor (Networking)					
	Yes	-	-		
	No	0.48	0.20,	1.13	0.093
as.factor (Technology_adoption)					
	Yes	-	-		
	No	0.94	0.44,	1.98	0.869
as.factor (Business_skills)					
	Yes	-	-		
	No	0.34	0.11,	1	0.052
as.factor (Marketing)					
	Yes	-	-		
	No	0.1	0.03,	0.29	**5.43e-05 *****
Trust		1.6	0.80,	3.4	0.201
Interaction		4.04	1.25,	13.6	**0.021081 ***
Empowerment		2.96	1.38,	6.61	**0.006378 ****

[1] OR = Odds Ratio, CI = Confidence Interval

*Significant Codes: 0 '***'0.001 '**'0.01 '*'0.05 '.'0.1 ' '1*

Results in Table 4 shows that access to finance have a significant positive association with CSA adoption (P<0.001, OR1=3.23). The odds ratio of 3.23 implies that smallholders who have access to finance are approximately 3.23 times more likely to belong to the medium and high level of CSA adoption. This implies a strong positive association between access to finance and the likelihood of CSA adoption. Results in

Table 4 shows that input subsidies have a significant positive association with CSA adoption (P=0.001, OR1=3.66). The odds ratio of 3.66 implies that smallholders who receive input subsidies are about 3.66 times more likely to belong to medium and high levels of CSA adoption. This indicates a strong positive association between input subsidies and the likelihood of CSA adoption.

Results in Table 4 shows that perceptions regarding training have a significant positive association with CSA adoption (P<0.006985, OR1=2.03). The odds ratio of 2.03 indicates that smallholders who perceive that training was effective are likely belong to the medium and high levels of CSA adoption. This suggests a moderate positive association between training and the likelihood of CSA adoption. Results in Table 4 shows that Labor has a significant and positive relationship (P=0.001, OR1=8.97) with CSA adoption. The odds ratio of 8.97 indicates that smallholders who have reliable and empowered labor are nearly nine times more likely to be in the medium and high levels of CSA adoption. This suggests a strong positive association between labor and the likelihood of CSA adoption.

Belonging to a farmers' group that advocates marketing is significantly associated with higher categories of CSA adoption (P<0.001, OR1=0.1). The odds ratio of 0.1 suggests that smallholders who are part of a farmers' group advocating marketing are ten times less likely to belong to medium and higher categories of CSA adoption. This indicates a strong negative association between membership in this type of group and CSA adoption (Table 4).

Interaction has a positive and significant association with higher categories of CSA adoption (P=0.021081, OR1=4.04). The odds ratio of 4.04 indicates that smallholders who engage in interaction are over four times more likely to belong to higher categories of CSA adoption compared to those who do not engage in such interaction. This suggests a strong positive association between interaction and the likelihood of being in higher categories of CSA adoption (Table 4).

Results in Table 4 shows that empowerment also has a significant positive association with CSA adoption (P=0.006378, OR1=2.96). The odds ratio of 2.96 suggests that smallholders who feel empowered are nearly three times more likely to belong to medium and higher categories of CSA adoption. An odds ratio greater than 1 indicates a positive association, meaning that as empowerment increases, the likelihood of CSA adoption also increases.

Discussion

Access to finance is enhanced when smallholders are able to save, obtain loans, secure reliable funding sources, and have a smooth transaction processes when accessing credit accounts. This financial access is essential for covering the costs associated with adopting CSA technologies. While some expenses like labor and storage arise later, many CSA technologies necessitate upfront investments in infrastructure such as certified seeds, organic fertilizers and installation of irrigation equipment's. Failure to access finances in a timely manner to procure these inputs presents a significant obstacle for economically disadvantaged smallholders. These findings align with those of (Gikonyo et al., 2022), who similarly discovered that access to funds among farmers in the Central region of Kenya significantly influenced the adoption of CSA technology.

Receiving subsidies for inputs significantly benefits smallholders by reducing financial burdens associated with CSA adoption, making it more accessible and appealing. These subsidies, by making inputs more affordable or even free, lower the financial obstacles that might deter smallholders from embracing CSA practices. Furthermore, subsidies may encourage smallholders to explore new CSA technologies, leading to increased adoption rates. However, excessive reliance on subsidies could lead to market inefficiencies and dependency among smallholders, potentially jeopardizing the long-term sustainability of agricultural development efforts. It's crucial for development partners to enhance subsidy programs by ensuring that smallholders receive inputs of the right quality, quantity, and timing, thereby promoting CSA technology adoption. These findings align with the research conducted by (Ouédraogo et al., 2019), which reported a significant association between access to input subsidies and the adoption of CSA technologies in Mali.

When smallholders believe that the training they receive is helpful and impactful they become empowered to invest in even complex farm technologies. This could be because training provides individuals with the knowledge and skills necessary to understand and engage with the CSA technology, leading to increased confidence and motivation to participate. Additionally, training may also help individuals overcome any barriers or uncertainties they may have about CSA adoption. Tailored training programs to the needs and priorities of smallholders enhances their perceived relevance and applicability, increasing the likelihood of adoption.

Training programs that incorporate hands-on learning experiences, demonstrations, and field visits can be particularly impactful in empowering smallholders to adopt CSA technologies. Seeing firsthand how these practices work in the real-world reinforces the value and feasibility of adoption, motivating smallholders to apply what they've learned on their own farms. Training programs provide opportunities for smallholders to interact with peers, extension officers, and project implementers, fostering supportive networks and peer learning opportunities. Positive interactions and shared experiences within these networks contribute to smallholders' sense of empowerment by providing encouragement, feedback, and mutual support in adopting CSA technologies. This finding is consistent with (Zakaria et al., 2020), who found that training programs had a positive influence on farmers' probability of adopting improved farm practices in Ghana. Similarly, (Serote et al., 2021) found that training was significant and contributed to the high percentage of knowledge access and adoption among smallholders in South Africa.

Smallholders with access to dependable labor for tasks such as planting, weeding, and harvesting are more likely to adopt CSA practices. A reliable labor force ensures timely completion of agricultural activities, enhancing the efficiency of CSA technologies. Certain CSA methods, like agroforestry and organic farming, often demand more labor-intensive approaches compared to conventional farming. Adequate labor resources enable farmers to effectively implement these practices, including tasks such as mulching and intercropping. Moreover, having well-trained and dependable labor contributes to the effective implementation of CSA technologies. Establishing a dependable labor force cultivates community and cooperation within farming communities, strengthening social networks and mutual aid mechanisms. This collaborative spirit extends beyond labor tasks to encompass knowledge exchange, resource sharing, and collective decision-making, all of which support the adoption and longevity of CSA practices. Similar results were found by (Gebremariam et al., 2021) in Ethiopia.

Encouraging marketing efforts within farmers' groups can play a vital role in promoting and facilitating the adoption of CSA among farmers. Through group platforms, members can engage in intra-group sales or combine their produce to collectively negotiate contracts and sell in larger quantities. Effective communication of the benefits of CSA, such as resilience to climate change and improved yields, can further incentivize farmers to embrace these practices. Despite this, the study did not find conclusive evidence that marketing within smallholder communities utilizes social networks and peer influence to drive CSA adoption. However, when farmers witness their peers successfully implementing CSA and reaping its benefits, they may be more inclined to follow suit. Marketing initiatives that showcase local success stories and testimonials can help shift social norms towards greater acceptance of CSA practices within the community. Similar findings were also reported by (Ahmed & Mesfin, 2017), who found that marketing was significant in the adoption of CSA technology.

Interaction of smallholders with various entities such as extension officers, middlemen, KSCAP officials, and friends correlates with higher levels of CSA adoption. These interactions likely facilitate the exchange of knowledge, resources, and support, thereby promoting the adoption of CSA technologies. Such interactions may deepen understanding of the benefits of CSA, strengthen community bonds, and foster ongoing engagement and support for CSA adoption. These findings are consistent with those of (Nato, et al., 2016), who reported that interaction was significant in the adoption of CSA technology among farmers in four counties in Kenya.

Empowerment for smallholders stems from their involvement and partnerships with project implementers, which encompass training sessions, interactions within farmers' groups and cooperatives, and engagement with the wider community. This involvement plays a pivotal role in the decision-making process regarding the adoption of CSA technologies. When individuals feel empowered, they are substantially more likely to embrace CSA practices. This inclination may be attributed to factors like heightened decision-making confidence, enhanced awareness of CSA benefits, or a deeper sense of community engagement and assistance. These findings align with the research conducted by (Nato, et al., 2016), who reported that empowerment significantly influenced the adoption of CSA technologies.

4.0 CONCLUSIONS AND RECOMMENDATIONS

Conclusions

CSA adoption appears to involve three major components the individual, community, and technology (tools for production enhancement). However, the study suggests that human needs and capabilities predominantly influence adoption decisions. While community resources provide a framework for adoption, actual adoption is driven by socialization, evidenced by interactions, and empowerment, rather than mere membership in a farmers' association. Smallholder farmers are more likely to adopt CSA practices when they are empowered and experience mutually beneficial interactions with fellow CSA participants, which reinforce positive choices.

Recommendations

Creating financial products tailored for smallholders is key to advancing the uptake of CSA technologies. Addressing gaps in input subsidies is vital to lower costs and motivate more farmers to adopt CSA technologies. Farmers training are crucial for equipping farmers with the knowledge to implement CSA technologies effectively. Strategies to enhance labor mobilization can bring significant benefits. Promoting networking and information sharing among farmers can disseminate best practices and boost adoption rates. Lastly, combining the CCF with Social Capital Theory offers a more detailed understanding of the factors influencing CSA adoption, emphasizing the interaction between various types of capital and social dynamics.

Institutional Review Board Statement: The study was approved by the Ethical Review Committee (ERC) of Pwani University, Kenya (ERC/PhD/005/2022).

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