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Drivers for adoption of climate smart agriculture technologies in Karnataka: An economic analysis

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Abstract

The study conducted in Southern Karnataka State focused on assessing the factors responsible for the adoption of climate-smart agriculture technologies among farmers in Chikkaballapur and Tumakuru districts. The research employed a systematic multistage purposive and snowball sampling technique to select 180 farmers, including adopters and non-adopters of climate smart agriculture technologies. The objective of the study is to identify the factors influencing the adoption of climate smart agriculture technologies. Data was collected through personal interviews, and analytical tools such as the Probit Model and output-elasticities were utilized to analyze the factors influencing adoption. Results revealed significant positive relationships between adoption of technologies and variables such as education (0.33), contact with extension agents (1.55), membership in organizations (3.39), access to weather information (2.90), participation in training (2.96), and farm income (3.13). These findings underscore the importance of institutional support, knowledge dissemination, and economic factors in driving adoption decisions. Overall, the study emphasizing the need for targeted interventions to promote sustainable agricultural practices in the region. This study suggests that the agricultural policy makers and implementers of climate smart technologies should recognize the complementarity among smart practices in order to intensify their adoption among farmers and disseminate technologies in other parts of the country thus, coping with the adverse effects of climate change.

Keywords: Factors, adoption, variables, sustainable agriculture, adverse effects

1. Introduction

Climate change is one of the most significant challenges facing humanity in the 21st century, impacting various sectors, including agriculture. Agriculture is inherently dependent on climate conditions, and the adverse effects of climate change are already evident in declining crop yields, changing precipitation patterns, and increased pest and disease pressures. In response to these challenges, the concept of climate-smart agriculture (CSA) has emerged, aiming to sustainably increase agricultural productivity, enhance resilience, and reduce greenhouse gas emissions. Among the sectors most vulnerable to the consequences of a changing climate, agriculture stands out as a vital lifeline for global food security. Agriculture, inextricably linked to climate conditions, must adapt to the changing environment while simultaneously mitigating its own contribution to greenhouse gas emissions. In this context, the concept of climate-smart agriculture (CSA) has emerged as a comprehensive approach that seeks to foster agricultural productivity, resilience, and sustainability, all the while reducing its carbon footprint.

Climate change represents a highly intricate environmental and societal challenge that is currently confronting the world. Developing countries, in particular, are significantly impacted due to unsustainable land management, land degradation, and greenhouse gas emissions from terrestrial ecosystems-all of which are closely linked to climate change. These changes have led to a decline in agricultural production, posing a serious threat to food security (IPCC, 2023) [2]. Furthermore, developing regions are experiencing climate change effects in the form of irregular and inconsistent rainfall patterns, more frequent and severe floods and droughts, increased rates of pests and diseases, and unpredictable agricultural planting seasons. As a consequence, production costs have risen, adversely affecting crop and livestock output (Kangogo *et al*. 2020) [12].

CSA encompasses a wide range of practices, technologies, and strategies designed to adapt to and mitigate the impacts of climate change while promoting sustainable agricultural development. These include improved irrigation systems, drought-resistant crop varieties, precision farming techniques, agroforestry, and soil conservation practices, among others. While the potential benefits of CSA are well-documented, the adoption of these technologies by farmers, especially smallholders in developing countries, remains a complex and multi-faceted challenge.

1.1 Socio-Economic Factors

Agricultural practices are deeply intertwined with the socio-economic conditions of farmers. Smallholder farmers, in particular, often face financial constraints, limited access to credit, and fragmented landholdings. These factors can hinder their ability to invest in and adopt new CSA technologies, which may require upfront costs and technical knowledge. Studies have shown that the availability of financial resources and credit facilities can significantly influence the adoption of CSA practices (Khatri *et al*., 2017) [13]. Additionally, farmers' risk perceptions and attitudes towards innovation play a crucial role in their willingness to adopt new technologies. Understanding the socio-economic context is, therefore, essential to devise inclusive and effective policies that promote CSA adoption among smallholders.

1.2 Knowledge and Information

Access to reliable information and knowledge about CSA technologies is fundamental for farmers to make informed decisions. Effective extension services, farmer training programs, and knowledge-sharing platforms can bridge the information gap and facilitate technology adoption. Furthermore, scientific evidence, case studies, and success stories can help build trust in new technologies and encourage farmers to experiment with innovative practices. Disseminating climate information, weather forecasts, and early warning systems can also empower farmers to make climate-resilient decisions, such as adjusting planting dates or selecting appropriate crop varieties.

1.3 Institutional and Policy Support

The role of institutions and supportive policies cannot be overstated in facilitating CSA adoption. Stable and favourable policy frameworks that incentivize sustainable agricultural practices and provide clear property rights can encourage farmers to adopt CSA technologies (Gornott *et al*., 2020) [9]. Furthermore, well-functioning agricultural extension services and research institutions can provide technical support and guidance to farmers. Strengthening agricultural value chains, market linkages, and agribusiness opportunities can enhance the economic viability of CSA practices, making them more attractive to farmers.

1.4 Climate Risks and Adaptation Strategies

The severity and frequency of climate-related risks strongly influence farmers' decision-making processes. Regions facing recurrent droughts, floods, or heat waves may be more receptive to CSA technologies that offer drought-resistant crops or water-efficient irrigation systems (Hassan *et al*., 2019) [16]. Understanding farmers' local adaptation strategies and integrating them with CSA practices can lead to more contextually relevant and acceptable solutions. The limited adoption of CSA technologies can be attributed to various factors, including socioeconomic status, farm characteristics, gender-specific aspects, access to resources, availability of agricultural and climate information services, institutional characteristics, and farmers' cognitive traits, such as their risk-taking behavior. Due to these barriers, farmers are more inclined to rely on less productive traditional methods.

The adoption of climate-smart agricultural technologies is crucial for building resilience and sustainability in the face of climate change. However, numerous factors influence farmers' decisions to adopt these technologies, making it a complex and context-specific process. This paper seeks to shed light on the key factors influencing CSA adoption, drawing from literature and climate reports. By understanding the interplay of socio-economic conditions, knowledge availability, institutional support, and climate risks, policymakers and stakeholders can design targeted interventions to promote CSA adoption among smallholder farmers. Accelerating the uptake of climate-smart agricultural technologies is essential to secure food and livelihood security while fostering a more climate-resilient and sustainable future.

To address these issues, the study utilizes household-level data from 90 adopters and 90 non-adopters of CSA technologies was collected in southern Karnataka, India. This paper aims to explore and analyze the factors influencing the adoption of climate-smart agricultural technologies, drawing insights from the existing literature and climate reports. The adoption of CSA technologies is a critical aspect of enhancing agricultural productivity and sustainability, particularly in regions vulnerable to climate change. By understanding the barriers and drivers that shape farmers' decisions to adopt or reject these technologies, policymakers, researchers, and agricultural practitioners can design targeted interventions to accelerate CSA adoption and foster resilient agricultural systems.

2. Materials and Methods

The present study was confined to the Southern Karnataka State. For the present study the systemized multistage purposive and snowball sampling techniques was used to select the sample farmers. In the two districts *viz*., Chikkaballapur and Tumakuru districts were selected based on extent of adoption of climate smart agricultural technology interventions and diversity in the socio-economic characteristics.

During the village selection process, experts from the Agriculture Technology Application Research Institute (ATARI) and KVK scientists were consulted to identify villages where climate-smart agriculture technologies were either partially or fully adopted. The criteria for village selection included vulnerability to climate change and susceptibility to drought. Ultimately, two villages with adopted climate-smart agricultural technologies and two villages with non-adopters were chosen for the study. To collect data from the selected villages, the researchers used snowball sampling to identify 45 climate-smart agricultural technology adopters from each adopted village and 45 non-adopters from each non-adopted village. Consequently, the study included a total of 90 climate-smart agricultural technology adopters and 90 non-adopter farmers, resulting in a sample size of 180 farmers for the study.

2.1 Description of the study area

The study was carried out in two districts of Southern

Karnataka (Fig.1). The Chikkaballapur district has a total geographical area of 638 km^2. As per the 2011 census, the total population of the district was 12,55,104 with a population density of persons per km2 and literacy rate was 64 percentage. The district experiences a semi-arid climate characterized by typical monsoon tropical weather with hot summers and mild winters. The average minimum temperature is 19.33 °C and maximum temperature is 31.33 °C. Whereas, Tumakuru district has a total geographical area of 10,597 km^2 and it is divided administratively into 10 taluks. As per the 2011 census, the total population of the district was 26,78,980 with a population density of 252 persons per square kilometer and the literacy rate was 75.14 percentage. The region experiences a tropical savanna climate, characterized by distinct wet and dry seasons. The monsoon season in Tumakuru usually begins in June and lasts until September. During this time, the region receives the majority of its annual rainfall, with an average of 780 mm of precipitation. Tumakuru district has maximum and minimum temperatures of 37 °C and 18 °C, respectively. The soils of the district are mostly sandy, sandy loam and red sandy loam.

2.2 Data collection

The study focused on two districts, namely Chikkaballapur and Tumakuru, situated in southern Karnataka. These districts were chosen because of their active engagement in adopting climate-smart agricultural technologies at the farm household level.

To gather information for the study, primary data was utilized as the main source. The primary data was collected through personal interviews with farmers who had embraced climate-smart agricultural technologies under the NICRA project. Additionally, non-adopter farmers were also interviewed using well-structured, pre-tested, and comprehensive schedules specifically designed for this study.

2.3 Analytical tools used

a. Probity Model

The empirical specification of market choices can be modelled through probit regression analysis. The probit model is a statistical probability model with two categories in the dependent variable (Liao). Probit analysis is based on the cumulative normal probability distribution. The binary dependent variable, y, takes on the values of zero and one. The outcomes of y are mutually exclusive and exhaustive. The dependent variable, y, depends on k observable variables xk where k=1,…, K (Aldrich and Nelson). While the values of zero and one were observed for the dependent variable in the probit model, there was a latent, unobserved continuous variable, y*.

$$y^* = \sum_{k=1}^{K} + \beta^k X^k + \varepsilon \qquad (1)$$

ε is $(0,\sigma^2)$

The dummy variable, y, was observed and was determined by y* as follows

y = {1 if y* > 0, 0 otherwise} (2)

The point of interest relates to the probability that y equals one. From the above equations, we see that:

$$\mathrm{Prob}\,(y=1) = \mathrm{Prob}\,(\sum_{k=1}^{K} \beta_x X_k + \varepsilon > 0$$
$$= \mathrm{Prob}\,(\varepsilon > -\sum_{k=1}^{K} \beta_x X_k$$
$$= 1 - \Phi(-\sum_{k=1}^{K} \beta_x X_k \qquad (3)$$

Where Φ was the cumulative distribution function of ε (Liao)

The probit model assumed that the data were generated from a random sample of size N with a sample observation denoted by i, i = 1,…,N. Thus the observations of y must be statistically independent of each other to rule out serial correlation. Additionally, it was assumed that the independent variables were random variables.

The Maximum Likelihood Estimation (MLE) technique was used to estimate probit model parameters. MLE focused on choosing parameter estimates that gave the highest probability or likelihood of obtaining the observed sample y. The main principle of MLE was to choose as an estimate of β the set of K numbers that would maximize the likelihood of having observed this particular y (Aldrich and Nelson).

The specification of the probit model was as follows

$$Y^*_{ki} = \beta_{k0} + \beta_{k1} X_1 + \beta_{k2} X_2 + \beta_{k3} X_3 + \beta_{k4} X_4 + \beta_{k5} X_5 + \beta_{k6} X_6 + \beta_{k7} X_7 + \beta_{k8} X_8 + \beta_{k9} X_9 + \beta_{k10} X_{10} + \varepsilon \qquad (4)$$

Where,

Y = Adoption of Climate Smart Agricultural Technologies (CSAT)

X_1 = Age (Completed years)

X_2 = Level of education (No. of formal years of education)

X_3 = Farm experience (Length of time spent in cultivating, Years)

X_4 = Total land holdings (Acres)

X_5 = Contact with extension agent (1 if yes, 0 otherwise)

X_6 = Respondent access to credit facility (1 if yes, 0 otherwise)

X_7 = Respondent membership in an organization (1 if yes, 0 otherwise)

X_8 = Respondent access to weather information (1 if yes, 0 otherwise)

X_9 = Respondent willingness to participate in climate change related programmes [1 if yes, 0 otherwise]

X_{10} = Income from farming (Rs. /annum)

In equation (4) Y^*_{ki} is a variable reflecting adoption of climate smart agriculture technologies by the i^{th} farmer with k denoting the adoption score (k = 0, 1).if k is 0 then farmer is not adopted a particular technology and if k is 1 then farmer is adopted a particular technology in the farm level.

The probit model was used both to estimate the impact of the independent variables on consumer behaviour regarding the purchase of fresh sweet corn. and to predict probabilities of change in consumer purchasing behaviour under several simulated variable levels.

b. Output-elasticities

Marginal effects of the explanatory variables at the mean could be obtained by:

Marginal effect of $X_i = \frac{dy}{dXi} * \frac{\overline{Xi}}{\overline{Y}}$ (or) $b_i * \frac{\overline{Xi}}{\overline{Y}}$ ……………….(5)

Where,

B = Parameter estimate (partial elasticity associated with

each independent variable)
$\bar{x}$ = Mean of independent variable
$\bar{y}$ = Mean of dependent variable

3. Results and Discussion

Table 1: Variables included in the model and their description

Variable	Parameter	Variable description	Variable type	Expected sign
Age	β_1	Age of the respondents (Years)	Continuous	+
Education	β_2	Education level (Years of formal education)	Continuous	+
Farm experience	β_3	Length of time spent in cultivating (Years)	Continuous	+
Total land holdings	β_4	Total land owned by the household (Acres)	Continuous	-/+
Contact with extension agent	β_5	Number of monthly visits to extension agents	Dummy	+
Credit accessibility	β_6	Respondent access to credit [1 if yes, 0 otherwise]	Dummy	+
Membership in an organization	β_7	Respondent membership in any organization [1 if yes, 0 otherwise]	Dummy	+
Access to weather information	β_8	Respondent access to weather information [1 if yes, 0 otherwise]	Dummy	+
Attended training related to climate change programmes	β_9	1 if the farmer has participated in any training, 0 otherwise	Dummy	+
Farm income	β_{10}	Income from farming (Rs. / annum)	Continuous	+/-

Summary statistics of all the independent variables used in the study are presented in Table 2. The average age of the adopters of CSA technologies was found to be 46 years which is less the non-adopters. This means that majority of the adopters are young and are in the brackets of economically active age group. The average years spent on formal schooling among adopters was 12.5 years. This implies that large section of adopters had high level of education compared with non-adopters whose education was around eight years. Additionally, adopters and non-adopter farmers are having farming experience of 21.17 and 23.01 years respectively. Average land holdings of adopters was 6.4 acres compared 4.6 acres in case of non-adopters. Which implies that adopters are having larger farm holdings compared to non-adopters. Also, about 90 percent of the adopters have access to weather related information against only 18 percent among non-adopters this gap is mainly due to the fact that adopters maintained well contact with agricultural organizations and access to information sources through KVK's television and mobile sources.

Table 2: Descriptive statistics of overall sample respondents of the study area

SI. No.	Variables	Pooled sample (n=180)				
		Adopters (n=90)		Non-adopters (n=90)		t-test
		Mean	SD	Mean	SD	
1.	Age	46.32	6.83	50.00	7.53	0.021**
2.	Education	12.54	3.49	8.02	3.15	0.001***
3.	Farm experience	21.17	10.47	23.01	9.26	0.429
4.	Total land holdings	6.47	5.93	4.69	2.44	0.031**
5.	Contact with extension agent	0.87	0.97	0.48	0.44	0.023**
6.	Credit accessibility	0.82	0.26	0.71	0.52	0.214
7.	Membership in an organization	0.88	0.31	0.32	0.46	0.001***
8.	Access to weather information	0.76	0.38	0.58	0.29	0.031**
9.	Participation in trainings	0.86	0.43	0.46	0.23	0.002***

Note: ***, ** and * indicates level of significance at 1, 5 and 10% level of probability

Furthermore, 86 percent of the adopters are engaged in attending training programmes related climate change and demonstration of innovative agricultural technologies compared to non-adopters in the study area. Among all the listed variables, variables such as age, education, total land holdings, contact with extension agent, credit accessibility and membership in an organization found to be positive and significant difference between adopters and non-adopters of CSA technologies in the study area as revealed by the t-statistics.

Since, institutional services are crucial factors influencing the famer's adoption decisions of CSA technologies. On average 82 percent of adopters have regular contact with agricultural extension agents to reap the benefits of innovative climate smart technologies in the study area. Approximately 92 percent of farmers in the study area had access to farm credit specifically for agricultural production purposes. The availability of farm credit is predominantly influenced by the involvement of NGOs and Village Savings and Loans Associations operating within the study area. About 88 percent of adopters having membership in organizations, which implies that adopters have more participation in social organizations intern helps in getting information about new production technologies.

The results of the probit model on factors influencing the adoption of CSA technologies was represented in table 3. The education status, contact with extension agent, membership in an organization and farm income of the farm households were found to have a positive relationship with the adoption of CSA technologies and they found to be statistically significant at one percent. Followed by access to weather information and participation in trainings were found to be positive and statistically significant at 5 percent level.

Table 3: Estimates of the probit model on factors influencing the adoption of climate smart agriculture technologies (n=180)

Variables	Sample respondents (n=180)		
	Co-efficient	**Std. Error**	**P-value**
Age	0.001	0.966	2.251
Education	0.336***	0.007	0.001
Farm experience	0.025	0.476	1.253
Total land holdings	0.253	0.316	3.251
Contact with extension agent	1.553***	0.004	0.002
Credit accessibility	2.842	0.032	0.102
Membership in an organization	3.394***	0.005	0.002
Access to weather information	2.902**	0.008	0.032
Participation in trainings	2.961**	0.015	0.050
Farm income	3.135***	0.016	0.001
Pseudo R^2	0.87		
Prob> chi2	0.00		
Log likelihood	-15.14		

Note: *** and ** denotes significant at 1% and 5% level of probability

Table 4, provides insights into how much household decisions regarding the adoption of CSA technologies have changed. Marginal effects, used to show these changes, express results as shifts in probabilities. This approach offers a more informative understanding compared to odds ratios and relative risks. The marginal effects suggest that expected education level of farmers increases by one percent leads 15.00 percent increase in the probability of adopting these technologies. The probable reason for this, is due to higher years of formal education perceived by farmers in the study area. Contact with extension agent found to be positive and significant at one percent level of probability. The marginal effects suggests that having contact with an extension agent leads to a 70 percent higher likelihood of adoption. Similar findings were reported by previous studies (Hailu *et al*., 2014) [11].

Table 4: Marginal effects of factors influencing the adoption of climate smart agriculture technologies

Variables	Sample respondents (n=180)		
	Marginal effect	**Std. Error**	**P-value**
Age	8.270	0.001	1.342
Education	0.015***	0.003	0.002
Farm experience	0.001	0.001	2.352
Total land holdings	0.011	0.011	1.232
Contact with extension agent	0.070***	0.016	0.001
Credit accessibility	0.129	0.049	0.073
Membership in an organization	0.154***	0.037	0.002
Access to weather information	0.132**	0.036	0.041
Participation in trainings	0.130**	0.045	0.043
Farm income	0.148***	0.061	0.001

Note: *** and ** denotes significant at 1% and 5% level of probability

The results of the probit model indicate that certain institutional variables have a significant influence on the adoption of climate smart agriculture technologies. These findings suggest that providing specific support and services to farming households through relevant agencies can contribute to higher adoption rates. For instances, it was found that farmers who were having membership in organization was found to be positive and significantly influencing he adoption of CSA technologies. The marginal effects show the probability of adoption increases by 15.4 percent. The results suggest that farmers who possess ample productive resources, such as having access to knowledge, skills, and awareness regarding weather information increases the adoption by 13.2 percent compared to farmers who lack such support. Studies conducted by (Mahama *et al*., 2020) [14] have confirmed the significance of access to credit facilities and extension services as crucial factors influencing farmers' opinions and decisions regarding the adoption of agricultural technology.

The results show that farmers participation in climate change related training have a significant and positive relationship with the adoption of CSA technologies. The marginal effects suggest that participation in training increases the likelihood of adoption by 13.00 percent. The probable reason for this, as noted in previous studies (Martey *et al*., 2021) [15], is that training provides an exposure mechanism that allows farmers to have a clearer understanding of the processes and procedures of the technologies. Similarly, membership in an organization and access to weather related information found to be positive and significantly influencing the adoption CSA technologies at one and 5 percent level of probability respectively. The analysis revealed a positive and statistically significant relationship between agricultural income and the adoption of CSA technologies at a significance level of one percent. This finding underscores the influential role of income in the decision-making process of the majority of farming households. The results suggests that an increase in the income generated from agriculture will lead to a 14.8 percent increase in the likelihood of adopting CSA technologies. These results are in line with the findings of (Awotide *et al*., 2022) [4].

4. Conclusion

The study highlights the significant role of socio-economic factors in influencing the adoption of CSA technologies among farmers. The analysis, based on a sample of 180 farmers from two districts in Southern Karnataka, reveals key factors influencing CSA technologies adoption and their respective impacts. The findings underscore the importance of institutional support and resource access in driving the adoption of climate-smart agriculture CSA technologies among farming households. Specifically, policymakers should consider household socioeconomic, institutional, and parcel-specific factors that positively influence CSA technology adoption. Providing smallholder farmers with regular extension and advisory services should be prioritized, since the frequency of extension visits and services enable smallholder farmers to adopt more CSA practices. Besides, creating awareness and disseminating information about the impacts of climate change and benefits associated with adoption of CSA practices using various media outlets assists farmers in adopting CSA practices and, thus, coping with the adverse effects of climate change.

5. Competing Interests

Authors have declared that no competing interests exist.

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