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Determinants of Adoption of Climate Smart Agricultural Technologies among Farm Households in Southern Karnataka, India

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The Climate change and its effects on agriculture pose major concerns for achieving a food-secure economy, particularly in developing countries like India. Furthermore, the carbon footprints resulting from agricultural activities are also a significant concern for the future climate. This study made an attempt to analyse the factors influencing the adoption of climate smart agricultural technologies among farmers in Chikkaballapur and Tumakuru, districts of Southern Karnataka using primary data collected from 180 randomly selected farm-households comprising 45 adopters and 45 non-

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adopters of climate smart agricultural technologies from each district. The data was analysed by fitting probit model to assess the factors influencing the adoption of climate smart agricultural technologies. The empirical results revealed that education (0.51), land holdings (0.63), credit accessibility (3.83), membership in organization (2.47), access to weather information (4.10), attended training (2.00) and farm income (0.49) were positive and significant relationship with the adoption of climate smart agricultural technologies in Chikkaballapur district. Similarly, in Tumakuru district age (0.14), contact with extension agent (2.78), credit accessibility (2.01), membership in organization (2.75), access to weather related information (2.16), participation in training (2.93) and farm income (0.34) was positive and significantly influenced the adoption of climate smart agricultural technologies among farm households. Whereas, age (-0.14) and land holdings (-0.39) of the respondents were negatively influenced the adoption in Chikkaballapur and Tumakuru districts, respectively. The findings, suggests that more emphasis should be given to increase awareness on innovative technologies and most importantly the institutional factors place a crucial role in enhancing the adoption of climate smart agricultural technologies in the study area among the farming community.

Keywords: Adopters; non-adopters; factors; awareness; changing climate; CSA technologies.

1. INTRODUCTION

The agriculture sector plays a vital role in enriching India's economy. In the recent years, the agriculture sector has been facing various challenges such as yield plateaus, soil degradation, and water stress, high imports on oilseeds, nutrition deficiency, volatile prices, inadequate infrastructure linkages, post-harvest loss, and information asymmetry. However, adverse climate changes remain one of the most significant issues faced by this sector [1]. According to a report, India lost approximately 5.04 million hectares of crop area due to cyclones, floods, cloudbursts, and landslides. Such calamities have had a severe impact on farmers, especially small farmers who constitute close to 85 per cent of the total farmers in India. Thus, there is a dire need for smart agriculture in India. About 800 million people in South Asia would be prone to climate change scenarios such as floods, cyclones, droughts and heatwaves, including India. Under carbon-intense climate change scenarios, India's per capita Gross Domestic Product (GDP) is projected to decline by 9.8 per cent by 2050. Additionally, climate-induced yield losses ranging from 4.5 to 9 per cent would result in an annual GDP loss of 1.5 per cent [2].

The last few years have witnessed rapid transformations of Indian agriculture, prompted in part by erratic weather patterns and extreme temperatures across the country's diverse climate zones. These innovations have been supported by a series of reforms and a robust policy framework. Farmers in India are adopting new farming practices, sharing information, and applying technology to address climate change. Several institutions with expertise in climate-smart agriculture, in both the private and public sectors, are working with farmers to develop and implement climate-responsive solutions. India has emerged as a significant player in addressing climate change. India has led several knowledge exchange and technical assistance programs helps to transform the agricultural systems of other countries. With India's presidency of the G20 this year, the Agriculture Working Group is focusing on climate-smart strategies to address food insecurity and crop productivity and promoting greater international cooperation. India should invest in working with others in the region to strengthen their institutional capacity and provide context-specific innovations and technology. International cooperation and collective action hold great promise for tackling the climate crisis by transforming agricultural techniques and food systems and making countries and communities more resilient [3].

Climate change poses significant challenges to agricultural systems worldwide, and India is no exception. As one of the world's largest agricultural producers and home to a substantial rural population, India faces the urgent need to adapt and mitigate the impacts of climate change on its farming sector. In this context, the adoption of climate-smart agricultural technology has emerged as a potential solution to enhance the resilience, productivity, and sustainability of Indian agriculture. Climate-smart agricultural technology refers to a range of innovative practices, tools, and approaches that help farmers adapt to climate change and reduce greenhouse gas emissions. It encompasses various techniques such as precision farming, agroforestry, conservation agriculture, improved irrigation systems, and the use of climate information and early warning systems. However, the widespread adoption of climate-smart agricultural technology in India is influenced by several factors, which shape the dynamics of its implementation and success.

Economic considerations play a crucial role in the adoption of climate-smart agricultural technologies. Indian farmers, especially smallholders, often face financial constraints and limited access to credit. The affordability and cost-effectiveness of adopting new technologies, including their potential to generate higher incomes and reduce production risks, significantly impact their uptake. Government subsidies, incentives, and financial support programs can play a vital role in encouraging farmers to adopt climate-smart technologies by reducing their financial burden. Furthermore, availability and accessibility of information and knowledge about climate-smart agricultural practices are pivotal. Many farmers in India, particularly those in remote rural areas, may lack awareness of the benefits and potential of these technologies. Strengthening extension services, promoting farmer-to-farmer knowledge sharing networks, and leveraging digital platforms can enhance information dissemination and create awareness, empowering farmers to make informed decisions regarding technology adoption. Additionally, the specific agro ecological and socio-cultural context of different regions in India influences the adoption of climate-smart agricultural technologies. The implementation of intensive agriculture, coupled with subsidies on essential inputs such as irrigation, electricity, and fertilizers, along with supportive pricing policies, encouraged farmers to embrace new technologies with limited regard for the potential long-term consequences of this exploitative approach on a broader scale [4].

The diversity of agro climatic zones, cropping patterns, and farming systems across the country requires context-specific approaches to technology selection and implementation. Tailoring technologies to suit local conditions and considering farmers' cultural and social preferences can enhance their acceptance and adoption. Adoption of climate smart agricultural (CSA) practices has been widely recognized as a promising and successful alternative to lessen the adverse impacts of climate change [5].

Theoretically, farmers need to maximize profits to adopt a typical or a combination of CSA practices. Farmers' adoption of CSA practices remains low in developing countries, including India. CSA practices and technologies, such as conservation agriculture and agroforestry continue to be under adopted by Indian smallholder farmers due to lack of financial resources for initial investments and existing insecure land tenure system **(**Negera, *et al*., 2022). Therefore, a better knowledge of factors that influence farmer's adoption behaviour is critical for developing policies that will sustainably increase the uptake of CSA practices. Empirical evidences indicate that smallholder farmers' adoption of CSA practices is greatly influenced by socio-economic, farm characteristics, institutional, access to basic infrastructure services, informational and technology awareness, social capital and climate-related factors [6]. The rising population and changing diets have created a huge pressure on land in India. Farmers are struggling to keep up as crop yields level off, soil degradation rises, water shortage increases, biodiversity declines, and natural calamities become more frequent. Furthermore, agriculture accounts for almost 14 per cent of India’s total greenhouse gas emissions. Climate-smart agriculture (CSA) can help transform agri-food systems in a responsive manner and mitigate the devastating effects of climate changes while producing food and energy in a sustainable manner. Farmers in India are gradually realising the benefits of CSA. CSA is an integrated approach that aims to achieve three outcomes simultaneously: increased productivity and income, enhanced resilience (adaptation) and reduced emissions (FAO, 2013 and FAO, 2018a).

1.1 Highlights of the Study

Earlier studies on adoption of CSA practices in India concentrated mainly on factors affecting a specific CSA practice. However, farmers are frequently presented with a variety of technologies that can be used in combination as complements or substitutes to mitigate and adapt to climate change. Thus, one of the current study's contributions is modelling CSA practice adoption while taking into account the interdependence between them. Besides, the farmers adopt different level of CSA practices. Examining the intensity of factors influencing the adoption of CSA technologies at farmer’s level using probit model is the second contribution of this paper.

1.2 Increased Productivity

The objective is to enhance nutrition security and increase incomes, particularly for the 75 percent of the world's poor population residing in rural areas, heavily dependent on agriculture for their livelihoods. This will be achieved by increasing the production and quality of food.

1.3 Enhanced Resilience

The goal is to enhance resilience against droughts, pests, diseases, and other climate-related risks and shocks while also strengthening the ability to adapt and thrive amid longer-term challenges, such as shortened seasons and unpredictable weather patterns.

1.4 Reduced Emissions

The focus is on reducing emissions associated with each unit of food produced, preventing agricultural-driven deforestation, and exploring methods to sequester carbon from the atmosphere.

Climate-smart agriculture, which encompasses the three main dimensions of sustainable development: economic, social and environmental, i.e. sustainably increasing agricultural productivity and incomes; adapting and building resilience to climate change; and reducing greenhouse gas emissions. It is an approach for developing agricultural strategies to secure sustainable food security under climate change. It is vital that climate-smart agriculture takes the local context and cultural and social sensitivities into account, and ultimately listens to the local community about the approach that best fits their reality. One of the institutions leading the adoption of climate smart agriculture is the International Atomic Energy Agency (IAEA). The IAEA, in cooperation with the Food and Agriculture Organization of the United Nations (FAO), supports this integrated approach to addressing the causes and effects of climate change, by monitoring agrochemical inputs for improving food safety; developing innovative land and water management technology packages; and enhancing carbon sequestration through innovative land-water management practices. Nuclear technology can be used to support climate smart agriculture in several ways: to assess the impact of climate change on agriculture; to gauge the impact of agricultural practices on climate change; to develop technologies for adaptation, building resilience to climate change; and improve agriculture practices to support climate change mitigation [2]. With this background objective is to study the determinants of adoption of CSA technologies among farm households in Southern Karnataka was taken up.

2. MATERIALS AND METHODS

2.1 Conceptual Frame Work

The conceptual model explains the factors influencing the adoption of climate smart agricultural technologies in the context of changing climate especially in Southern Karnataka. The treatment variable in this study is adoption of Climate-Smart Agricultural (CSA) technologies. The broad definition of CSA technologies includes the integration of different farming/agronomic practices and systems, as well as the improvement of input use, such as seeds, fertilizers, water, etc. It includes typical technologies like climate stress tolerant varieties, rain water management, and organic manuring, which are classic examples in technology adoption studies [7] as well as practices like intercropping, conservation agriculture, manuring and water harvesting, elsewhere discussed under terms like sustainable practices or conservation agriculture. The adoption decisions are mainly depending on many socioeconomic factors like age, education, farming experience, contact with extension agent etc. and other demographic features of farm households.

Essentially, CSA technologies and practices contribute to the adaptation of farmers to the effects of climate change and more importantly, it helps the resource poor farmers to address climate change issues such as extreme drought, extreme precipitation, and changes in seasonal timing. In this regard, the ultimate aim of CSA technologies is to simultaneously increase agricultural productivity and resilience in the face of climate change, while at the same time reducing greenhouse emissions from agricultural systems [8].

2.2 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 296 persons per km^2 and literacy rate was 62.04 percentage. 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.

2.3 Sampling Design

The study employed both multistage purposive and snowball sampling techniques to collect quantitative and qualitative data. Purposive sampling was used to select the districts where the adoption of climate-smart agricultural technologies was implemented under the National Innovations in Climate Resilient Agriculture **(**NICRA) project through Krishi Vigyan Kendras (KVK's) and snowball sampling was performed while selecting the respondent's in the study area.

During the selection process of villages, officials from the Agriculture Technology Application Research Institute (ATARI) and KVK scientists from the selected districts were consulted. These experts helped to identify villages where climate-smart agriculture technologies were either partially or fully adopted. The selection criteria for these villages were based on their vulnerability to climate change and their proneness to drought, followed by extent of adoption of adoption of CSA technologies at farmer's field level. In total, two adopted villages and two non-adopted villages were selected for the study. To collect the data from the selected villages, a snowball sampling technique was employed to identify 45 Climate-Smart Agricultural (CSA) technology adopters from each adopted village and 45 non-adopters were selected from each non-adopted village. In total, 90 CSA technology adopters and 90 non-adopter farmers were chosen as respondents, resulting in a sample size of 180 farmers for the study.

2.4 Data Collection

The study was carried out in two districts viz., Chikkaballapur and Tumakuru, located in the Southern Karnataka. The selection of these districts was based on the adoption of climate-smart agricultural technologies at the farm household level.

Primary data was used for the purpose of the study. The data was collected from the farmers' those who adopted climate smart agricultural technologies under NICRA project and non-adopter farmers through well structured, pre-tested and comprehensive schedules exclusively prepared for the study, by personal interview method.

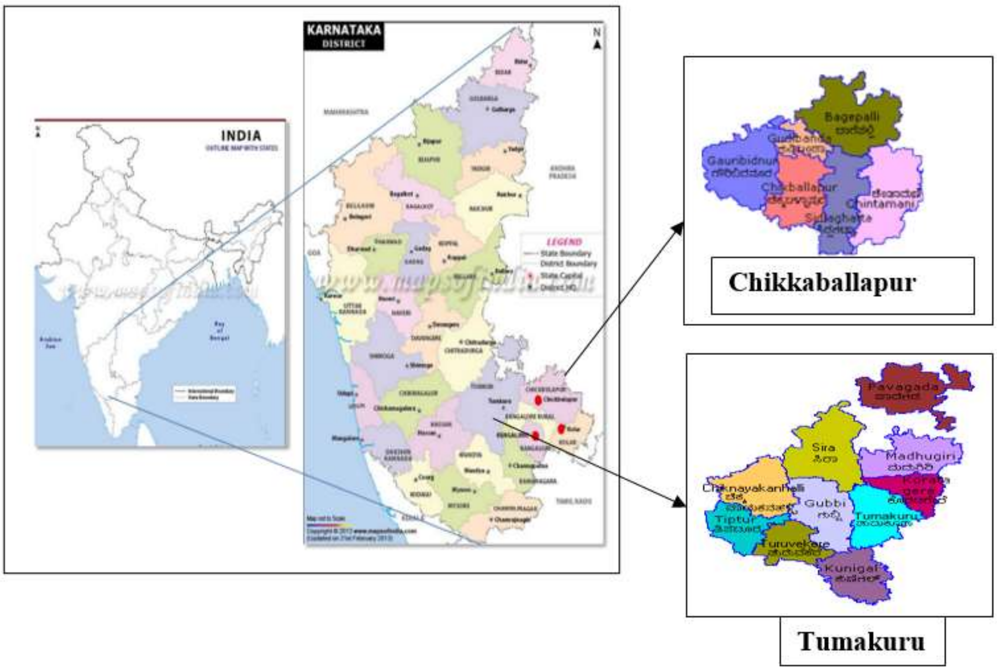

Fig. 1. Map indicates the study area
Source: mapsofindia.com

2.5 Analytical Tools Used

2.5.1 Probit 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 X_k 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*.

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

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:

$$\begin{aligned} \text{Prob}\,(y=1) &= \text{Prob}\,(\textstyle\sum_{k=1}^{K} \beta_x\ X_k + \varepsilon > 0 \\ &= \text{Prob}\,(\varepsilon > -\textstyle\sum_{k=1}^{K} \beta_x\ X_k \\ &= 1 - \Phi(-\textstyle\sum_{k=1}^{K} \beta_x\ X_k \end{aligned} \quad (3)$$

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

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

Where,
Y = Adoption of Climate Smart Agricultural (CSA) technologies
X_1 = Age
X_2 = Level of education
X_3 = Farm experience
X_4 = Total land holdings
X_5 = Frequency of contact with extension agent
X_6 = Respondent access to credit facility
X_7 = Respondent membership in an organization
X_8 = Respondent access to weather information
X_9 = Respondent willingness to participate in climate change related programmes
X_{10} = Income from farming

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 adoption of climate smart agricultural technologies and to predict probabilities of factors contributing to the adoption behaviour under several simulated variable levels.

2.5.2 Output-elasticities

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

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

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

3.1 Summary Statistics of the Sample Farmers Used in the Study

The Table 1, represents descriptive statistics of the sample respondents in the Chikkaballapur district. The variables of interest include were age, education, family size, farm experience, total land holdings, contact with extension agent, credit accessibility, membership in an organization, access to weather information, and participation in trainings.

In Chikkaballapur district, average age of the adopters of CSA technologies was found to be 50 years. This means that majority of the adopters were young and are in the brackets of economically active age group. The average years spent on formal schooling among adopters was 12 years. This implies that large section of adopters had high level of education compared with non-adopters whose education was around eight years. Adopters had a slightly higher mean family size of 4.71, while non-adopters had a slightly lower mean family size of 4.48. Additionally adopters and non-adopter farmers were having farming experience of 23.02 and 20.60 years respectively. This suggests that adopters had higher farming experience compared to non-adopters. Adopters had a higher mean total land holding of 7.10 acres, while non-adopters had a lower mean total land holding of 4.18 acres. This indicates that on average adopters tend to have larger land holdings compared to non-adopters.

Adopters had a higher mean score of 0.84, indicating a relatively high level of contact with extension agents. Non-adopters, on the other hand, had a lower mean score of 0.42. Both adopters and non-adopters had relatively high mean scores for credit accessibility, with adopters having a slightly higher mean score of 0.80, compared to non-adopters i.e. 0.71. Adopters had a higher mean score of 0.86, indicating a higher level of membership in organizations. Non-adopters, on the other hand, had a lower mean score of 0.55. Furthermore, 88 per cent of the adopters were engaged in Participation in trainings programmes related to climate change and demonstration of innovative agricultural technologies compared to non-adopters in the study area.

In Chikkaballapur district, contact with extension agent, membership in an organization and access to weather related information were found positive and significant at one per cent level of probability. Whereas, total land holdings was positive and significant at five percent level of probability. Additionally age and farm experience were positive and significant at 10 per cent level of probability which was revealed by T-test statistics.

The Table 2, represents descriptive statistics of the sample respondents in the Tumakuru district. The results was found that the mean age of the respondents was 47 and 51 years respectively between both the groups. This suggests that majority of the adopters were comes under young and economically active group.

Table 1. Descriptive statistics of sample respondents of the study area

Sl. No	Variables	Chikkaballapur district				T-test
		Adopters (n=45)		Non adopters (n=45)		
		Mean	SD	Mean	SD	
1.	Age	50.04	4.07	47.37	6.88	1.83*
2.	Education	12.02	4.53	8.39	2.82	4.52
3.	Family size	4.71	1.85	4.48	1.32	0.65
4.	Farm experience	23.02	7.39	20.60	8.97	1.39*
5.	Total land holdings	7.10	8.26	4.18	2.50	2.27**
6.	Contact with extension agent	0.84	0.36	0.42	0.49	3.94***
7.	Credit accessibility	0.80	0.40	0.71	0.45	0.97
8.	Membership in an organization	0.86	0.43	0.55	0.50	3.66***
9.	Access to weather information	0.91	0.88	0.71	0.45	2.47***
10.	Participation in trainings	0.88	0.31	0.35	0.48	6.50

*Note: ***, ** and * indicates level of significance at one, five and 10 per cent level of probability*

Table 2. Descriptive statistics of sample respondents of the study area

Sl. No	Variables	Tumakuru district				T-test
		Adopters (n=45)		Non-adopters (n=45)		
		Mean	SD	Mean	SD	
1.	Age	47.02	8.03	51.02	7.95	2.43***
2.	Education	10.13	3.31	8.26	3.52	1.75*
3.	Family size	5.13	1.47	4.66	1.70	1.45
4.	Farm experience	21.88	8.90	24.02	9.62	-1.08
5.	Total land holdings	4.85	2.01	4.37	2.18	1.03
6.	Contact with extension agent	0.82	0.38	0.33	0.47	5.70
7.	Credit accessibility	0.84	0.36	0.60	0.49	1.83*
8.	Membership in an organization	0.77	0.42	0.53	0.50	2.82***
9.	Access to weather information	0.86	0.34	0.71	0.45	1.82*
10.	Participation in trainings	0.68	0.46	0.31	0.46	3.82***

*Note: ***, ** and * indicates level of significance at one, five and 10 per cent level of probability*

The years spend in formal education was found to be 10 years for adopters and this was relatively higher compared to non-adopters of CSA technologies i.e. eight years. On average family size was five members in both the groups. Whereas, farming experience was higher among non-adopters compared to adopters. This was due to fact that non-adopters comes under the age group of 51 years hence farming experience was found higher compared to adopter of CSA technologies. Additionally land holdings was found to be 4.85 and 4.37 acres across both the group of respondents.

Institutional factors place a major role in influencing adoption of climate smart agricultural technologies. The variables such as contact with extension agent, credit accessibility, membership in an organization, access to weather information and participation in trainings are found to be higher among adopters compared to non-adopters in the study area.

The variables such as age, membership in an organization and participation in trainings was found to be positive and significant at one percent level of probability. Whereas, education, credit accessibility and access to weather information was positive and significant at 10 per cent level of probability based on the T-statistic values.

3.2 Determinants of Adoption of Climate Smart Agricultural Technologies in the Study Area

3.2.1 Selection of variables and their meaning for probit model

Variables included in the probit model was presented in Table 3. The variables such as age, education, farm experience, total land holdings and farm income were continuous and quantitative in nature. Whereas, other variables like extension contact, credit access, membership, access to weather information and participation in training programmes are taken as dummy variables for the analysis. The dependent variable, adoption of climate smart agricultural technologies was regressed against the stated independent variables.

The results of probit model on determinants of adoption of CSA technologies in the study area calculated using the model represented in the methodology section (Equation 3) are presented in Table 4. The results revealed that several socioeconomic, institutional, and climate-related factors had a significant influence on the farmers' adoption decision in Chikkaballapur districts. These factors will be discussed in this section. The diagnostic statistics shows good fit of the model, as indicated by highly significant Chi-square statistics. The results showed that the explanatory variables included in the model were relevant and jointly explain the adoption decisions of farmers.

In Chikkaballapur district, the coefficient of age was negatively significant at 5 per cent ($p<0.005$) level of probability in adoption of CSA technologies. This implies that older the farmers are less likely to adopt climate smart agricultural technologies. It has been noted that older one becomes more risk averse. It was also due to the fact that farmers tend to be more conservative as the age increases and had a negative attitude towards the adoption of innovative technologies which will decrease their productivity.

The coefficient of land holdings found to be positive and significantly influencing the adoption at 5 per cent level of probability. It implies that has landholdings increases adoption of CSA technologies increases. It was due to the fact the if the farmers holds larger area under cultivation, proportion of area kept for constructions bunds, and farm ponds on farms increases compared those farmers having small holdings. These finds are consistent with the results reported by [9]. However, access to weather related information found to be positive and significantly influencing the adoption of CSA technologies in the study area. These findings are consistent with the results reported by [10].

Furthermore, education was found to be positive and significantly affecting the adoption of CSA technologies. This implies that farmers who possess higher formal school education tend to adopt more innovative CSA technologies compared to farmers who are having less formal school education. And membership in an organization found to be positively significant at 1per cent level of probability. It was due to fact the farmers in the study area have formed Village Climate Risk Management Committee (VCRMC) under NICRA project which influences the adoption of new CSA technologies. Additionally, Participation in trainings and farm income was positive and significantly influencing the adoption of CSA technologies at 1 per cent level of probability.

The results of probit model on determinants of adoption of CSA technologies in the study area Tumakuru district, was represented in the Table 5. All the independent variables included in the model were regressed on dependent variable. The results revealed that variables such as access to credit facilities and income from farm has positive and significant influence on adoption of CSA technologies at five per cent level of probability.

Table 3. 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 visit 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	+
Participation in training 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	+/-

Table 4. Estimates of probit model on determinants of adoption of CSA technologies in the study area

Variables	Parameters	Chikkaballapur district	
		Coefficient	***P*-value**
Age	β_1	-0.144**(0.068)	0.034
Education	β_2	0.511***(0.511)	0.011
Farm experience	β_3	0.253(1.220)	0.836
Land holdings	β_4	0.632**(0.315)	0.045
Contact with extension agent	β_5	4.328(1.879)	0.321
Credit accessibility	β_6	3.837(1.713)	0.025
Membership in an organization	β_7	2.470***(0.689)	0.000
Access to weather information	β_8	4.105**(1.914)	0.032
Participation in training programmes	β_9	2.000***(0.822)	0.005
Farm income	β_{10}	0.490***(0.076)	0.000
Pseudo R^2	0.85		

Note: 1. Prob> chi2 =0.00, Log likelihood = -8.93
2. Figures in the parentheses indicates standard error
*3. ***, ** and * indicates level of significance at 1%, 5% and 10% level of probability*

Table 5. Estimates of probit model on determinants of adoption of CSA technologies in the study area

Variables	Parameters	Tumakuru district	
		Coefficient	***P*-value**
Age	β_1	0.146* (0.084)	0.082
Education	β_2	0.023 (0.070)	0.74
Farm experience	β_3	0.015 (0.038)	0.681
Land holdings	β_4	-0.399* (0.238)	0.093
Contact with extension agent	β_5	2.780*** (1.226)	0.013
Credit accessibility	β_6	2.010* (1.000)	0.074
Membership in an organization	β_7	2.757*** (0.917)	0.043
Access to weather information	β_8	2.167*** (0.917)	0.018
Participation in training programmes	β_9	2.937 (1.075)	0.030
Farm income	β_{10}	0.344** (0.179)	0.05
Pseudo R^2	0.82		

Note: 1. Prob> chi2= 0.00, Log likelihood= -11.01
2. Figures in the parentheses indicates standard error
*3. ***, ** and * indicates level of significance at 1%, 5% and 10% level of probability*

The coefficient of access to weather related information was positive and significant at 1per cent level of probability. This was due to the fact that adopter are getting weather information from village level weather station, where non-adopters do not have such facility related to weather information. And contact with extension agent and participation in trainings related to climate change and demonstration of CSA technologies found to be positive and significantly influencing the adoption of CSA technologies at 1per cent (P<0.001) level of probability in the study area. The coefficient of age was positive and significantly influencing the adoption decisions of CSA technologies in the study region at 10 per cent (P<0.10) level of probability. And land holdings and credit access found to be negatively significant in adoption of CSA technologies at 10 per cent level of probability.

To know the extent of changes in the household decision to adopt CSA technologies, marginal effects have been estimated (Table 6). Marginal effects are a way of presenting results as differences in probabilities, which is more informative than odds ratios and relative risks.

The result shows that the explanatory variables included in the model were relevant and jointly explain the adoption decision of farmers. In Chikkaballapur district, it could be inferred that younger age farmers more tend to adopt CSA practices compared to older farmers. As one per cent increase in the age of respondents from its

Table 6. Marginal effects of determinants of adoption of CSA technologies in the study area

Variables	Chikkaballapur		Tumakuru	
	Marginal effect	Std. Error	Marginal effect	Std. Error
Age	-0.008**	0.002	0.009*	0.004
Education	0.028***	0.007	0.001	0.004
Farm experience	-0.001	0.003	0.001	0.002
Total land holdings	0.351**	0.013	-0.026*	0.013
Contact with extension agent	0.240**	0.073	0.183***	0.058
Credit accessibility	0.149	0.074	0.112*	0.076
Membership in an organization	0.078***	0.001	0.081***	0.070
Access to weather information	0.171**	0.070	0.142***	0.043
Participation in training programmes	0.165***	0.053	0.193	0.043
Farm income	0.095***	0.039	0.036**	0.007

*Note: *** And ** indicates level of significance at one and five per cent level of probability*

mean level, adoption decrease by 0.8 per cent. But in case of Tumakuru district, age of respondent increases by one per cent from its mean level, the adoption increase by 0.9 per cent. It is due to the fact that adopters in Tumakuru district were young age farmers. As education level increases one per cent from its mean level, adoption will increase by 2.8 per cent in case of Chikkaballapur district. Total land holdings has positive and significant influence on adoption in Chikkaballapur district and it was negatively significant in Tumakuru district, as one per cent increase in land holdings, adoption decrease by 2.6 per cent due to the fact that larger area under arecanut plantations. Contact with extension agent has positive and significantly influencing the adoption in both districts. Thus, farmers who had access to extension services in the cropping season had higher probability of adopting these technologies than those who did not have access extension services. Extension officers are generally responsible for transferring technologies to the farmers. As one per cent increase in access to credit facilities found increase adoption by 11.2 per cent in Tumakuru district. However, credits may come with some terms and conditions that may favour the adoption of specific technologies other than several technologies. Consistently, (Imran *et al*., 2018) explained that adoption of CSA technologies were limited by low access to farm services such as credit.

Similarly, membership in an organization, access to weather-related information, participation in trainings, and farm income has increased the adoption of CSA technologies by 7.8, 17.1, 16.5 and 9.5 per cent, respectively in the Chikkaballapur district. These results are in line with [11]. Whereas, in the Tumakuru district, as one per cent increase in contact with extension agents, membership and access to weather-related information increases, adoption increased by 18.3, 8.1 and 14.2 per cent, respectively. Furthermore, credit accessibility (13.2 %) and farm income (3.6 %) has positive and significantly influenced the higher adoption rate at five per cent level of probability. Overall, the results confirmed that farmer's adoption decisions were influenced by socio-economic and demographic characteristics.

4. CONCLUSION

Climate change majorly affects the poor and marginal farmers who make their livelihoods from agriculture. Technology and climate smart practices can help to mitigate risks caused by climate change, among others. In this study we have investigated empirical analysis of the factors such as famer's socio-economic characters, farm characteristics and institutional factors that are influencing the adoption of CSA technologies using the probit model technique.

The farmers decision to adopt any CSA technologies are statistically significant and positively influenced by age, education, contact with extension agent, access to weather information, membership in any organization, access to credit facilities and income generated from farm activities in both the districts. Hence, there is a need to set up a proper institutional framework to demonstrate innovative climate-smart agricultural technologies to give hands-on training during field days and study tours, etc. Investing in educational programs and awareness campaigns, strengthening and expanding farmer groups and enhancing role of extension agents, dissemination of accurate and timely weather information on climate variables, increasing availability of training programs and government initiatives to diversify farmers' income sources can create a conducive environment for the widespread adoption of Climate-Smart Agriculture technologies.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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