Adaptation of farmers to climate-change and determinants of their adaptation decisions in South India

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Research Article

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Abstract

Agriculture, with its allied sectors, is the largest source of livelihood in India and now faces a serious challenge from climate-change. In this context, this study investigated, how farmers in India perceive climate-change, what adaptation strategies they practice, and major determinants of their adaptation decisions. Primary data forms the database collected from 400 sample farmers from southern States of India to employ Discriminant model and Multinomial Logit Model (MNLM). The results of Discriminant analysis revealed that off-farm income, income from agriculture and farming experience are the major discriminating variables with largest contributions to motivate the farmers for tackling climate-change. Findings from MNLM revealed that in addition to above three variables, access to climate-change information and education background of the farmers are also the important determinants in adoption of climate-change adaptation strategies viz., crop diversification, integrating crops with livestock, change in the planting date and adoption of soil and water conservation measures. The study highlighted increasing role of Government in the future to safeguard interests of farmers through offering a wide range of institutional, policy and technology support. Further, providing off-farm employment opportunities to the farmers is crucial to sustain their livelihoods, as such activities are less sensitive to climate-change.

1. Introduction

Environmental changes viz. climate change, land-use change and natural resource degradation have aggravated vulnerability of agricultural production across the countries in the world. Among these, climate change has emerged as the biggest developmental challenge especially for developing countries like India through disrupting the normal socio-economic settings, particularly of the poor (Sunita, 2009). Its adverse effects are much severe on agricultural sector in affecting both food and nutrition security and sustainable development. So, it is imperative on the part of farmers to face climate change in agriculture through following various adaptation strategies that demand collaborative efforts from different stakeholders. Of course, the major driving force for taking up climatic adaptation strategies comes from farmers' perceptions to tackle the climate change phenomenon.

India experienced a series of droughts (Figure 1) and the one in 1987 was one of the worst, with an overall rainfall deficiency of 19 per cent, which affected 59–60 per cent of the normal cropped area and a population of 285 million. This was repeated in 2002 when the overall rainfall deficiency for the country as a whole was again 19 per cent. Over 300 million people spread over 18 States are affected by drought along with around 150 million cattle. Food grains production registered an unprecedented steep fall of 29 m. tonnes. After 2002, the drought in 2018 is considered to be second severe one, affecting about 42 per cent of land area and 500 million people (almost 40% of the country's population). With the advent of climate change since 1990s (Sunita, 2009), failed monsoon is the primary reason for frequent droughts in India. Since it is not possible to avoid the adverse impacts of climate change (Figure 2), it is vital to promote adaptation strategies among the farmers to tackle it in their farm fields. Before this, it is essential to analyze their perceptions about climate change adaptation strategies and determinants of the same for their effective implementation. The earlier studies conducted in South Africa (Tshikororo et al, 2021), Ghana (Francis et al, 2021), Ethiopia (Belay et al, 2017), Uganda (Nabikolo et al, 2012), Fiji (John, 2008) etc., highlighted that farmers changed their cultivation practices as adaptation strategies in various ways viz., change in cropping calendar, crop varities, machinery for cultivation practices, crop diversification, integrating crops with livestock (farming systems approach), soil and water conservation practices etc. Even strategies such as System of Rice Intensification (SRI) and micro irrigation were adopted by the farmers to combat water scarcity situation. They also implemented strategies for coping with declining soil productivity through increasing organic manure application, compost making and application, crop rotation, crop residues retention (Belay, 2017; Tshikororo et al, 2021). In India, even the Government also started promoting formation of Farmer-Producer Organizations (FPOs), when a single farmer could not afford adaptation strategies (Naveen et al, 2019). However, the study conducted by Niles et al. (2016) revealed an interesting finding that the farmers' attitude and

perception towards climate change do not correlate to their actual adoption. So, it is equally important to analyze the determinants of different climatic adaptation strategies being followed by the farmers besides their perceptions to tackle climate change phenomenon. With this background, this study was focused on better understanding of perceptions and practices followed by the farmers to tackle climate change in four Southern States viz., Andhra Pradesh, Telangana, Tamil Nadu and Karnataka. As no prior research on these lines was conducted earlier in Southern parts of India, this study is certainly a contributing one to highlight farmers' perceptions as one of the major critical elements for tackling climate change and to identify major determinants for practicing various adaptation strategies.

2. Review Of Literature:

Francis and Tsunemi (2015) analyzed socio-economic factors that influence farmers' adaptation to climate change in agriculture. The empirical results of the logistic regression model showed that education, household size, annual household income, access to information, credit and membership of farmer-based organization are the most important factors that influence farmers' adaptation to climate change. However, the researchers identified unpredictability of weather, high farm input cost, lack of access to timely weather information and water resources are the major constraints of farmers' adaptation to climate change.

Abrham et al (2017) analysed the smallholder farmers' climate change adaptation strategies and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia. Findings of the study revealed that the farmers' capacity to choose effective adaptation options is influenced by household demography, as well as positively by farm size, income, access to markets, access to climate information and extension, and livestock production. So, the researchers suggested the need to support the indigenous adaptation strategies with a wide range of institutional, policy, and technology support. Creating opportunities for non-farm income sources is equally important, as such activities are less sensitive to climate change. Furthermore, providing climate change information, extension services, and creating access to markets are crucial.

Alex et al (2017) analysed the household determinants that contribute to climate change adaptation strategies in the Mount Rwenzori area of South Western Uganda. A Multinomial Logistic Model (MNLM) was used to assess the drivers of farmers' choice for adaptation practices, factors influencing the choice of adaptation, and barriers. The study concluded use of different crop varieties, tree planting, soil and water conservation, early and late planting, and furrow irrigation are the major adaptation practices. The findings of Discrete choice model indicated that age of the household head, experience in farming, household size, climate change shocks, land size, use of agricultural inputs, landscape position (location), and crop yield varied significantly ($p > 0.05$) and influenced farmers' choice of climate change adaptation practices. Researchers concluded that inadequate information on adaptation methods and financial constraints are the major barriers for adaptation and hence, suggested increasing support from government and other stakeholders.

Francis et al (2020) investigated the factors influencing adaptation strategies to climate change in the Black Volta Basin of Ghana. Multi-variate probit model revealed that gender, age, household size, farmer-based-organizations membership, farm income, years of education, districts of location of respondents, farm size and climate change awareness are the major factors that influenced households' adaptation to the changing climate. The researchers suggested that improving household heads' adaptive capacity and increasing investments in climate-resilient programmes by governmental and non-governmental organizations should deserve special attention.

Mpho et al (2021) analyzed the farmers' socio-economic characteristics towards tackling climate change in Limpopo Province, South Africa. They study the influence of socio-economic characteristics such as age, gender, farming experience and level of education on farmers' perception about tackling climate change through employing Discriminant Analysis. The study concluded that formal education, agricultural education, age group, farming experience and off-farm occupation significantly contributed towards farmers' perception regarding tackling of climate change.

3. Methodology

3.1. Sampling procedure: This study was conducted in four States of Southern India viz., Andhra Pradesh, Telangana, Tamil Nadu and Karnataka, as they occupy prominent positions in the cultivation of major crops like paddy, maize, groundnut, cotton, chillies, sunflower, tobacco, tomato, banana, cashew, coconut and cardamom. More than half of the Gross Area Sown (GAS) across these states viz., Andhra Pradesh (52%), Telangana (63%), Tamil Nadu (54%) and Karnataka (75%) is under rainfed condition. Further, in all these States, the share of marginal and small farmers in the total number of holdings was more than 80 per cent (2011 census). In Andhra Pradesh (Ananthapuramu, (540 mm), Telangana (Jogulamba Gadwal, 533 mm), Tamil Nadu (Tiruppur, 600.3 mm) and Karnataka (Chitradurga, 507.4 mm) are the major drought prone districts due to scanty (normal) rainfall (India Meteorological Department, 2019).

According to Yamane (1967), the minimum sample size in the study should be:

$$n = \frac{Z^2 p(1-p)}{e^2} = \frac{\left((1.96)^2 0.5\left(1-0.5\right)\right.}{0.05^2} = 384.16$$

So, this study involved a cross-sectional survey of 400 sample farmers @ 100 random sample from each of the above four districts during 2019-20. Data are collected relating to perceptions of them towards tackling climate change and for identifying the major determinants for climate change adaptation (drought coping) strategies followed by them in the study area. A structured questionnaire was employed among the sample farmers with the assistance from local Agricultural Officers, who interacted directly with the farmers at the local level.

In the context of present study, two groups of farmers were made viz., farmers willing to tackle climate change (Yes = 1) and farmers not willing to tackle climate change (No = 0). As per the survey, 256 farmers are willing and practicing climate change adaptation strategies and remaining 144 farmers are not willing to tackle climate change. Socio-economic characteristics of sample farmers (Table 1) were hypothesized to contribute to discriminating between the two categories of farmers.

3.2. Empirical Models:

3.2.1. Discriminant analysis: This multivariate statistical technique is employed (Tshikororo et al, 2021; Nguyen, 2017), as it is used to classify farmers into two (or more) mutually exclusive and exhaustive categories or groups based on a set of independent variables. That is, discriminant model is used to distinguish between two categories of farmers for tackling climate change: willing to tackle climate change and non-willing to tackle climate change coded as 1 and 0 respectively. These two possible categories are defined by number of factors, which simultaneously influence the farmers' willingness to tackle climate change. In this study, information related to independent variables (Table 1) are used to calculate discriminant score Z for a given farmer as follows:

$$Z_i = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 + \beta_4 * X_4 + \beta_5 * X_5 + + \beta_6 * X_6 + \beta_7 * X_7 + \varepsilon$$

where, Z is the discriminant score that maximizes the distinction between the two categories.

Table 1
Description of explanatory variables used in the discriminant analysis

Variable	Name	Type of measure	Expected sign
X1	Farming experience (FE)	Quantitative variable (Years)	+
X2	Trainings on climate-change adaptation strategies (TRG)	Dummy; (0 = No, 1 = Yes)	+
X3	Age of the farmer (AGE)	Quantitative variable (Years)	+
X4	Extension contacts (EC)	Dummy; (0 = No, 1 = Yes)	+
X5	Off-farm income (OFFI)	Quantitative variable (Rs/-)	+
X6	Farm Size (FS)	Quantitative variable (hectares)	+
X7	Agricultural Income (AI)	Quantitative variable (Rs/-)	+
Dependent variable: Climate-change adaptation strategies (CC): Dummy; (1 = Yes, 0 = No)			

Before running discriminant analysis, it is important that data used must be independent and normally distributed (Khemakhem and Boujelbene, 2015). So, Kolomogorov- Smirnov test was employed to prove the data are normally distributed. Further, multicollinearity among the independent variables was also tested through computing Pearson's correlation matrix. As the highest absolute value of correlation coefficient between each of variable is less than 0.7, multicollinearity problem was ruled out in this study. In the next step, discriminant analysis (direct method) is applied to the sample data.

3.2.2. Multinomial Logit Model (MNLM): To analyze the determinants for practicing different climate-change adaptation strategies viz., crop diversification (shift towards drought-resistant crops), integrating crop with livestock, change planting date and adoption of soil and water conservation practices, MNLM was employed (Belay, 2017; Diallo, 2020; Alex et al, 2017). Table 2 shows the description and expected signs of explanatory variables used in this study. The estimation of MNLM was conducted by normalizing one category, which is named as 'base category'. The adaptation measures were grouped into above four major categories because, farmers used more than one strategy, and the base category was 'No adaptation strategy.' That is, Climate-change adaptation strategy – the dependent variable (Dummy), 4 = crop diversification, 3 = integrating crop with livestock, 2 = change planting date, 1 = adoption of soil and water conservation practices and 0 = No adaptation strategy.

Table 2
Description of explanatory variables used in the MNLM

Variable	Name	Type of measure	Expected sign
X1	Farming experience (FE)	Quantitative variable (Years)	+
X2	Trainings on climate-change adaptation strategies (TRG)	Dummy; (0 = No, 1 = Yes)	+
X3	Age of the farmer (AGE)	Quantitative variable (Years)	+/-
X4	Extension contacts (EC)	Dummy; (0 = No, 1 = Yes)	+
X5	Off-farm income (OFFI)	Quantitative variable (Rs/-)	+
X6	Farm Size (FS)	Quantitative variable (acres)	+/-
X7	Agricultural Income (AI)	Quantitative variable (Rs/-)	+
X8	Access to climate information (AC)	Dummy; (0 = No, 1 = Yes)	+
X9	Access to market (AM)	Dummy; (0 = No, 1 = Yes)	+
X10	Education (EDU)	Quantitative variable (Years)	+
X11	Livestock ownership (LO)	Dummy; (0 = No, 1 = Yes)	+

4. Results And Discussion:

4.1. Descriptive Statistics: The descriptive analysis (Table 3) revealed a mean age of 45 years with a Standard Deviation (SD) of 7.97 for farmers who are practicing climate adaptation strategies and a mean age of 44 years and a SD of 8.09 for farmers not willing to take up climate adaptation strategies. With respect to number of trainings (TRG) received on the importance of climate adaptation strategies, contacts with local extension officers (EC), farming experience (FE) and farm size (FS), the result did not reveal much variation between the two categories of adoption. However, it is interesting that both off-farm income and agricultural income of farmers practicing climate adaptation strategies (Rs.26503 (US$ 355.94) & Rs. 120717 (US$1621.23) respectively) are considerably higher compared to farmers not willing to practice climate adaptation strategies (Rs. 19811 (US$266.06) and Rs. 119900 (US$1610.26) respectively). This showed that the farmers practicing climate adaptation strategies are benefitted through getting higher off-farm income and agricultural income. On an average, the respondents had 45 years of age with 13 years of FE and derive around 83 per cent of annual income from agriculture and remaining 17 per cent from off-farm sources.

Table 3
Descriptive statistics (Group means) across selected categories of farmers

CC		Mean	Std. Deviation
No (0)	FE	11.69	3.08
	TRG	0.52	0.50
	AGE	44.19	8.09
	EC	0.13	0.33
	OFFI	19810.80	10324.70
	FS	3.42	2.43
	AI	119900.00	13729.10
Yes (1)	FE	13.20	2.89
	TRG	0.56	0.50
	AGE	45.08	7.97
	EC	0.14	0.41
	OFFI	26502.60	11843.50
	FS	3.55	2.50
	AI	120717.00	12844.10
Total	FE	12.66	3.04
	TRG	0.54	0.50
	AGE	44.76	8.01
	EC	0.13	0.38
	OFFI	24093.50	11755.60
	FS	3.50	2.47
	AI	120423.00	13158.20

4.2.: Model Adequacy: From the two categories considered in the dependent variable, the software has distilled one discriminant function ie., Function 1. Results of the tests for model adequacy are presented through Table 4. The Box M test (regarding equality of population covariance matrices of the two categories of dependent variable) showed that F_{cal} value (1.345) was found non-significant (P= 0.105) implying equality of covariance matrices across the two categories ie., adopters and non-adopters. This gives a clue for the researcher to proceed further in the analysis.

There are many other tests that sufficiently classify the two categories. The Wilks Lambda (λ) test (testing the null hypothesis that means vectors of the two categories in the dependent variable are equal) inferred the value (0.102) is close to '0' indicating better discriminating power of the model. That is, lower the value of Wilks' λ, the higher is the significance of the discriminant function (0 value is most preferred one). The probability value for χ2 indicate that the discriminating power between two groups is highly significant (P = 0.000). This means that the discriminant function computed in this procedure is statistically significant at the 0.000 level and now the researchers can proceed to interpret the results. Other tests like Pillai's trace (to test the assumption of equality of the mean vectors for the three categories or

classes), Hotelling-Lawley trace (to test the assumption of equality of the mean vectors for the various classes) and Roy's Greatest Root (to test the assumption of equality of the mean vectors for the various classes) are also found significant (Tshikororo et al, 2021; Nguyen, 2017)

Table 4
Tests of model adequacy

Test Statistic	Value	F Value	DF1	DF2	P value
Box test (χ2 asymptotic approximation, -2Log(M))	38.444	1.345	28	315510.51	0.105
Wilks' λ	0.102	42.25**	7		0.000
Pillai's trace	0.116	6.414	8	391	< 0.0001
Hotelling-Lawley trace	0.131	6.414	8	391	< 0.0001
Roy's Greatest Root	0.131	6.414	8	391	< 0.0001
** - Chi-square value					
To know, whether a significant difference exists between the means of two groups, a one way ANOVA is carried out. Each of the predictor variable is treated as a dependent variable and the category of dependent variable as an independent variable and the results are present in Table 5. It is found that the significant difference is observed in case of FE, OFFI and AI for which the P-values are less than 5 per cent level of significance. However, in case of other predictors, no significant difference was observed (P-value > 0.05).					

Table 5
Tests of Equality of Group Means

Variable	Wilks' Lambda	F	df1	df2	Sig.
FE	0.943	24.004	1	398	0.000
TRG	0.998	0.682	1	398	0.409
AGE	0.997	1.121	1	398	0.290
EC	1.000	0.087	1	398	0.768
OFFI	0.925	32.199	1	398	0.000
FS	0.999	0.228	1	398	0.633
AI	0.999	0.355	1	398	0.032

Another way of evaluating the performance of the discriminant function is to investigate the eigenvalue and the canonical correlation coefficient (Table 6). An eigenvalue (0.113) indicates the proportion of variance explained ie., a large eigenvalue is associated with a strong function and hence, 100 per cent of the variance was explained. This shows that the function is highly significant and potential enough in classifying the categories. The canonical relation is a correlation between the discriminant scores and the levels of the dependent variable. A high canonical correlation coefficient (0.948) indicates a function that discriminates well between two categories of dependent variable and also infers no overlapping among them. Squaring the canonical correlation suggested that 89.8 per cent of the variation in the grouping variable was explained (Halagundegowda, 2017; Nguyen, 2017). As shown through Table 4, unexplained error is 10.2 per cent (Wilks' λ: 0.102). So, out of total variation, 89.8 per cent of the variability is explained by this model (canon $corr^2$ = 0.898). So, strong association is detected (canonical correlation = 0.948) between two groups namely, set of all independent variables and two categories of farmers (dependent variable).

Table 6
Eigenvalue for Statistical Significance

Functions	Canon Correlation	Eigen value	Variance	
			Prop	Cumulative
1	**0.948**	**0.113**	**1.000**	**1.000**

4.3. Relative Importance of the Discriminating Variables: Table 7 presents the summary data for the discriminant analysis and the analysis yielded one discriminant function for two categories of climate-change adaptation. The findings include both unstandardized and standardized discriminant (canonical) function coefficients and they are meant for evaluating the relative contribution of each of the predictor variables as discriminators between two categories. When predictors are measured in different units, the magnitude of an unstandardized coefficient provides little indication of its relative contribution to the discriminant function. So, standardizing the coefficients is necessary, so as to have a common scale of measurement for comparative purposes as all the predictor variables (Kumari, 2017).

Table 7: Summary of Unstandardized and Standardized Canonical Discriminant

Function Coefficients

Variables	Unstandardized coefficients	Standardized coefficients
	Function 1	Function 1
Intercept	-5.680	
FE	0.175	0.517
TRG	-0.170	-0.085
AGE	0.027	0.219
EC	0.319	0.122
OFFI	0.000	0.658
FS	0.045	0.112
AI	0.000	0.558

In the derived function, the sign indicates the direction of the relationship and magnitude indicate the extent of contribution to the group discrimination. It is important to note that the larger the standardized coefficient (b), the larger is the respective variable's unique contribution to the group discrimination (irrespective of the sign of the coefficient). All the predictors except TRG are positively influencing the discrimination of groups. It is further apparent from the analysis that OFFI (b5 = 0.658), AI (b7 = 0.558) and FE (b1 = 0.517) are the highest discriminating variables with largest contributions. This result means that appropriate attention should be given towards promoting off-farm employment opportunities, profitability of agriculture and as well as due recognition to the FE in order to motivate them to practice/implement climate-change adaptation strategies. So, by using the variables and the standardized coefficients, the required discriminant equation (discriminator) is shown below:

$$Z = 0.517\ FE - 0.085\ TRG + 0.219\ AGE + 0.122\ EC + 0.658\ OFFI + 0.112\ FS + 0.558\ AI$$

The classification results (Table 8) reveal that 79 per cent of respondents were classified correctly into 'Willing' or 'Non-willing' groups and this overall predictive accuracy of the discriminant function represents the 'hit ratio' (based on cross

validated set of data). Farmers willing to tackle climate-change were classified with slightly better accuracy (84.1%) than their counterpart (74.7%).

Table 8
Classification of results for the discriminant function

		CC	Predicted Group Membership		Total
			0.00	**1.00**	
Original	Count	0	82	17	99
		1	42	259	301
	%	0	82.8	17.2	100.0
		1	13.9	86.1	100.0
Cross-validated	Count	0	74	25	99
		1	48	253	301
	%	0	74.7	25.3	100.0
		1	15.9	84.1	100.0

4.4. Structure matrix: In addition to standardized coefficients, structural matrix is also used to check the relative importance of the predictors. This provides another way to study the usefulness of each predictor variable in the discriminant function. It indicates the product moment correlations between the discriminating variables and discriminant function. Factor loadings ≥0.30 is used as the cut-off between important and less important variable ie., if the structure coefficient is ≥0.30, it is considered meaningful (Halagundegowda, 2017; Kumari, 2017; Nguyen, 2017). The findings indicated that the structure coefficients with the highest relationship to function 1 were OFFI (0.846), AI (0.789) and FE (0.730). That is, these three predictors enjoy positive correlation with the function. Squaring the coefficient of a predictor will explain the proportion of variation in the dependent variable. For instance, OFFI can explain 72 per cent (= 0.846^2) variation in the dependent variable. With 0.30 as the cut-off point, the other predictors viz., TRG, AGE, EC and FS were not loaded on the discriminant function. That is, these predictors were, therefore, not significantly associated with climate-change adaptation strategies. Clearly, EC is the weakest predictor and suggests that it is not associated with adaptation strategies, but a function of other un-assessed factors.

Table 9
Structure matrix

Predictor	Function 1
FE	0.730**
TRG	-0.123
AGE	0.158
EC	0.044
OFFI	0.846**
FS	0.071
AI	0.789**

The group centroids are the averages of the Z values calculated by the estimated model, which can use to evaluate the expected position of the concerned farmers' categories. (Uddin, 2013). As can be seen in Table 10, the centroid of non-willing category is -0.447 and the centroid of the 'willing' category is 0.252. This implies that if someone's score on the discriminant function is positive (closer to 0.252), then that respondent is probably willing to tackle climate change. On the contrary, if a person's score on the discriminant function is negative (closer to –0.447), then the data probably came from the 'non-willing' category. On calculating the cut score (halfway between the two centroids) ie., -0.097 and if an individual person's score on the discriminant function (calculated by plugging in their scores on predictor variables) is above -0.097, then the respondent is probably from the 'willing' category. On the contrary, if the discriminant function score is below –0.097, then the respondent is probably from the 'non-willing' category.

Table 10
Functions at group centroids

CC	Function 1
0.00	-0.447
1.00	0.252

Finally, the performance of the model was studied using the Receiver Operating Characteristic (ROC) curve (Figure 3). The results showed a large Area Under the Curve (AUC) of 71.4 per cent and significant at 5 per cent level, which further affirmed that the model was correctly specified.

4.5. Determinants for climate-change adaptation strategies:

The findings of MNLM (Table 9) revealed that FE, AI, AC and EDU (at 1% level) and OFFI and AM (at 5% level) are significantly influencing the farmers to practice crop diversification towards less-water consuming and drought resistant crops. For integrating crops with livestock, FE, AI, AM and LO (at 1% level) and EC and FS (at 5% level) were the most significant factors. Change in planting date was significantly influenced by FE, AI and AC (at 1% level) and TRG and EDU (at 5% level). Regarding adoption of soil and water conservation practices, it was significantly influenced by FE, OFFI, AI and AC (at 1% level) and EDU (at 5% level). A close perusal of the table further revealed that FE and AI are the crucial factors that promote the farmers to take up the climate-change adaptation strategies in the selected States. The marginal effects of FE indicated that, for every one year increase, the probabilities of practicing crop diversification, integrating crop with livestock, change in planting date and adoption of soil and water conser vation practices are increased by 1.06, 0.03, 1.83 and 1.48 percents respectively. Similarly, the marginal effects of AI indicated that a unit increase in income can increase the likelihood of practicing crop diversification, integrating crop with livestock, change in planting date and adoption of soil and water conservation practices by 9.15, 8.51, 9.33 and 4.13 percents respectively. AC is another important variable that contributed to

Table 9
Parameter estimates of MNLM for climate change adaptation strategies by sample farmers

Variable	Crop diversification		Integrating crop with livestock		Change planting date		Adoption of soil and water conservation practices	
	Coefficient	Marginal effect ($\partial Y_j/\partial X_{ij}$)	Coefficient	Marginal effect ($\partial Y_j/\partial X_{ij}$)	Coefficient	Marginal effect ($\partial Y_j/\partial X_{ij}$)	Coefficient	Marginal effect ($\partial Y_j/\partial X_{ij}$)
FE	0.1015	0.0106**	0.0708	0.0026**	0.1136	0.0183**	0.0277	0.0148**
	(0.0432)	(0.0025)	(0.0264)	(0.0008)	(0.0632)	(0.0071)	(0.0019)	(0.0039)
TRG	0.2828	0.0372	0.1432	0.0126	0.3357	0.0302*	0.3624	0.0246
	(0.0167)	(0.0261)	(0.1305)	(0.04327)	(0.1408)	(0.0125)	(0.4956)	(0.0023)
AGE	-0.1158	-0.0052	-0.1747	-0.0168	-0.1499	-0.0082	0.1441	0.0024
	(0.1019)	(0.0033)	(0.1238)	(0.0031)	(0.0261)	(0.0067)	(0.0966)	(0.0015)
EC	0.8211	0.0978	0.4985	0.0156*	0.6735	0.0371	0.3458	0.0138
	(0.4019)	(0.0522)	(0.1957)	(0.0135)	(0.2878)	(0.0197)	(0.1266)	(0.0126)
OFFI	0.0013	0.0676*	-0.0516	-0.0152	0.0000177	0.0016	0.0239	0.0689**
	(0.0005)	(0.0281)	(0.0412)	(0.0458)	(0.000016)	(0.0038)	(0.0016)	(0.0251)
FS	0.0519	0.0068	0.0272	0.0267*	0.0033	0.0341	-0.1334	-0.0053
	(0.0597)	(0.0095)	(0.0032)	(0.0115)	(0.0011)	(0.0279)	(0.0977)	(0.0042)
AI	4.9312	0.0915**	0.0016	0.0851**	0.0321	0.09327**	0.0164	0.0413**
	(1.9678)	(0.0017)	(0.0001)	(0.0167)	(0.0012)	(0.0052)	(0.0053)	(0.0012)
AC	0.0129	0.0147**	0.3119	0.0053	0.1073	0.0236**	0.0816	0.0117**
	(0.0028)	(0.0046)	(0.3561)	(0.0465)	(0.0135)	(0.0064)	(0.0279)	(0.0024)
AM	0.0799	0.0161*	0.1411	0.0184**	-0.2388	-0.0288	0.8454	0.0343
	(0.0366)	(0.0072)	(0.0288)	(0.0071)	(0.4219)	(0.0511)	(0.8011)	(0.0219)
EDU	0.0159	0.0275**	-0.0428	-0.0059	0.0335	0.0028*	0.0933	0.0138*
	(0.0016)	(0.0099)	(0.0657)	(0.0093)	(0.0142)	(0.0012)	(0.0423)	(0.0059)

Note: ** - Significant at 1% level, * - Significant at 5% level

the adaptation options among the selected farmers. As expected, the findings showed that the farmers' access to climate-change information had impacted the likelihood for adaptation to climate-change through practicing crop diversification (1.47%), change in planting date (2.36%) and adoption of soil and water conservation practices (1.17%). This implies that the farmers who enjoy better access to climate change information (i.e., seasonal or mid-term forecasting) made better informed adaptation decisions. These findings are similar to the findings from various studies (Adeagbo, 2021; Belay, 2017; Halagundegowda, 2017; Tshikororo, 2021). As expected by the researchers, EDU and livestock rearing had a positive association across all climate-change adaptation strategies. Other determinants like AM (on crop diversification (1.61%) and integrating crop with livestock (1.84%)), FS (on integrating crop with livestock (2.67%)) and TRG (on change in planting date (3.02%)) have exerted significant positive influence on the adoption of climate-change adaptation strategies.

Variable	Crop diversification		Integrating crop with livestock		Change planting date		Adoption of soil and water conservation practices	
	Coefficient	Marginal effect ($\partial Y_j/\partial X_{ij}$)	Coefficient	Marginal effect ($\partial Y_j/\partial X_{ij}$)	Coefficient	Marginal effect ($\partial Y_j/\partial X_{ij}$)	Coefficient	Marginal effect ($\partial Y_j/\partial X_{ij}$)
LO	0.4141	0.0854	0.1998	0.0569*	0.2774	0.0496	0.9334	0.0549
	(0.3761)	(0.0663)	(0.0441)	(0.0053)	(0.4957)	(0.0447)	(0.5721)	(0.0408)
Constant	4.8531		10.5932		6.5866		6.303853	
	(1.9621)		(2.0886)		(2.2876)		(3.237694)	

Note: ** - Significant at 1% level, * - Significant at 5% level

the adaptation options among the selected farmers. As expected, the findings showed that the farmers' access to climate-change information had impacted the likelihood for adaptation to climate-change through practicing crop diversification (1.47%), change in planting date (2.36%) and adoption of soil and water conservation practices (1.17%). This implies that the farmers who enjoy better access to climate change information (i.e., seasonal or mid-term forecasting) made better informed adaptation decisions. These findings are similar to the findings from various studies (Adeagbo, 2021; Belay, 2017; Halagundegowda, 2017; Tshikororo, 2021). As expected by the researchers, EDU and livestock rearing had a positive association across all climate-change adaptation strategies. Other determinants like AM (on crop diversification (1.61%) and integrating crop with livestock (1.84%)), FS (on integrating crop with livestock (2.67%)) and TRG (on change in planting date (3.02%)) have exerted significant positive influence on the adoption of climate-change adaptation strategies.

Summary and Conclusions:

Climate-change is considered as one of the biggest threats to global agriculture and India, in particular. So, it is essential for the farmers to plan and resort for different climate-change adaptation strategies to stabilize their annual income and sustain in the farm business. Discriminant analysis revealed that OFFI, AI and FE are the highest discriminating variables with largest contributions. So, these variables are to be given due attention in the study area to motivate the farmers for practicing climate-change adaptation strategies. The findings of MNLM revealed that FE and AI are the major determinants that contribute towards adoption of selected climate-change adaptation strategies followed by AC, EDU and OFFI. These findings highlight that the role of Government is crucial in the ensuing years to safeguard the interests of farmers through a wide-range of institutional, policy and technology support. Among the above determinants, creating off-farm employment (income) opportunities to the farmers deserves special mention, as those activities are less sensitive to climate-change (Belay, 2017; Tshikororo, 2021). To conclude, the aspects like linking farmers to markets, improving access to climate-change information, knowledge about various climate-change adaptation strategies (long-term drought proofing measures) etc., should be included in the existing formal agricultural extension system of the Ministry of Agriculture and Farmers' Welfare and other line Ministries to benefit the farming community.

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Figures

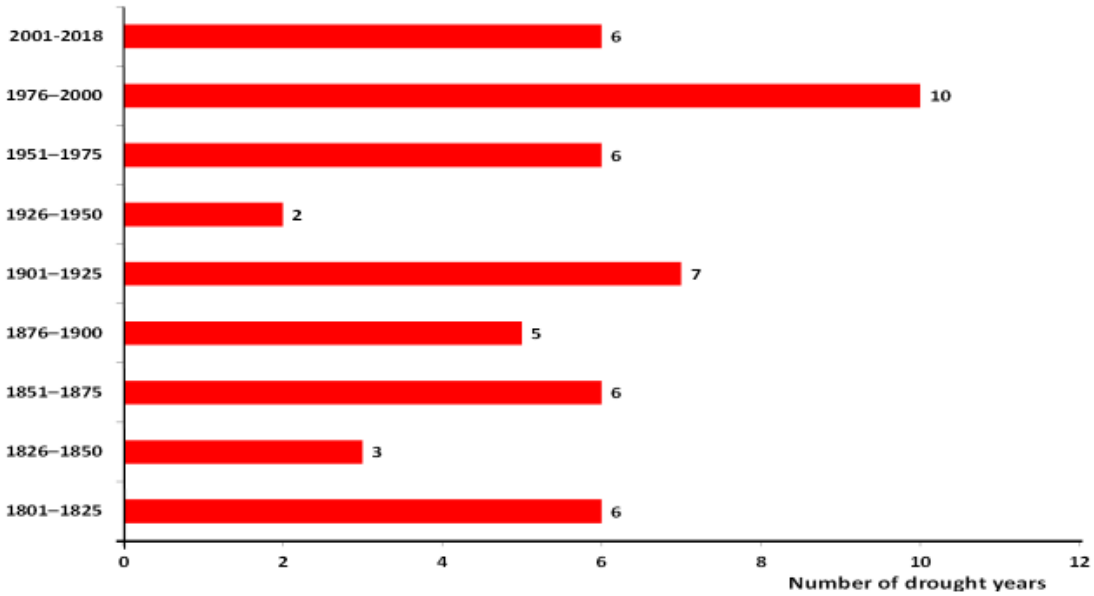

Figure 1

Number of Drought years in India since Past 200 years

Temperature Variability	Increase in annual temperature	1.7°C to 2.2°C
	Extreme temperature increase	1°C to 4°C
	Seasons may be warmer	2°C
Precipitation Variability	Mean increase in annual precipitation	7 to 20%
	Increase in monsoon precipitation	10 to 15%
	Number of rainy days	Decrease
Extreme events - Droughts	Groundwater table	Sharp drop
	Perennial rivers	Seasonal & Regular water stress
Extreme events - Floods	Exceeds the existing magnitude	10 to 30%
	Rise in sea surface temperature	2°C to 4°C
	Increase in cyclone intensity	10 to 20%
Sea level	Rises	1.33 mm/year

Figure. 2: Climate change projections for India by 2030

Figure 2

Climate change projections for India by 2030

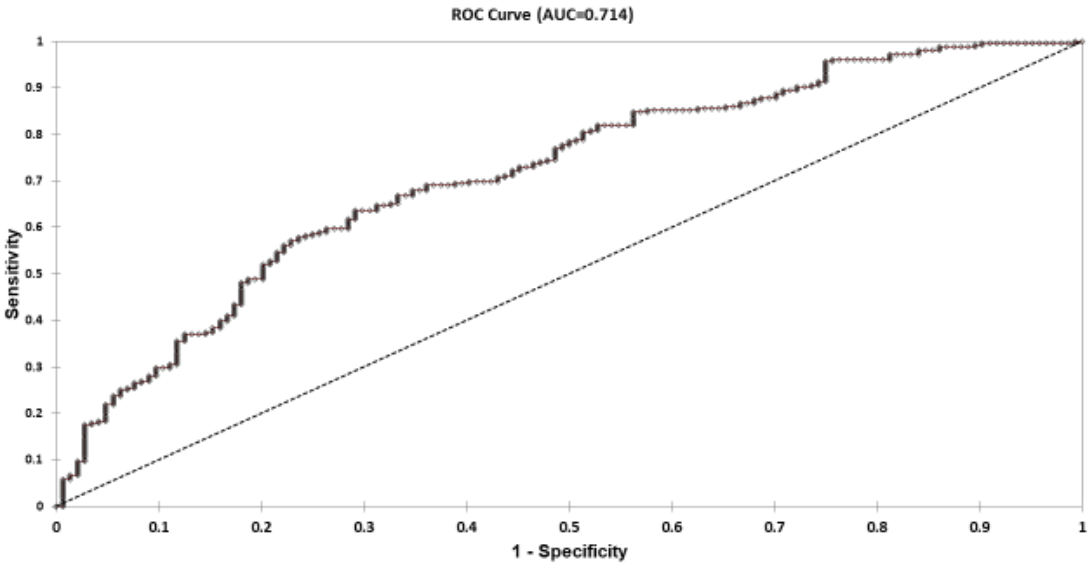

Figure 3: ROC Curve

Figure 3

ROC curve