Indian Journal of Agricultural Economics 79: 3 (2024):787-800
DOI:10.63040/25827510.2024.03.032

Drivers of Climate-Smart Practices Adoption: Evidence from Punjab

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ABSTRACT

The study investigates the factors influencing the adoption of climate-smart agricultural (CSA) practices among farmers in Punjab. The study uses a multistage sampling method to select 240 farmers from different agro-climatic zones, dividing them into adopters and non-adopters of CSA practices. Principal Component Analysis (PCA) was employed to develop a composite index, with Laser Land Levelling and Short Duration Varieties emerging as the most widely adopted practices. The adoption index showed that 50.85 per cent of farmers were medium adopters, 38.98 per cent were high adopters, and 10.17 per cent were low adopters of CSA practices. The study used a Tobit model to identify key factors influencing the adoption of CSA practices. The findings reveal that age, education, farm size, training, access to non-farm income, and mass media exposure significantly affect the likelihood of adoption. Middle-aged farmers with higher education levels, larger farm sizes, and more access to training and mass media are more inclined to adopt CSA practices. The study highlights the importance of targeted interventions, including farmer education and training, to enhance the adoption of climate-smart agricultural practices, which are crucial for improving agricultural resilience to climate change in Punjab

Keywords: Determinants of adoption, composite index of adoption, Tobit, Punjab agriculture

JEL codes: C24, O33, Q15

I

INTRODUCTION

The increase in global surface temperatures due to human activities, particularly through greenhouse gas (GHG) emissions, is a major factor driving global warming. The Intergovernmental Panel on Climate Change (IPCC) emphasizes that GHG emissions continue to rise, with unequal contributions stemming from energy use, land use, and varying consumption patterns across different regions and individuals (IPCC, 2023). Climate change has had serious impacts on food and water security, posing a challenge to achieving the Sustainable Development Goals (SDGs). While agricultural productivity has increased, climate change has slowed its growth over the past 50 years, exacerbating financial constraints and slowing economic development, especially in developing countries (Asseng et al., 2011). The effects of climate change on food security and human health are both direct and indirect. Direct effects include declines in crop productivity and yields (Lobell et al., 2011), while indirect effects involve reduced water availability (De Fraiture and Wichelns, 2010; Mancosu et al., 2015; Komarek et al., 2020), increased pest invasions (Reddy, 2013), and lower labor efficiency (Lanfranchi et al., 2014). Changes in temperature and humidity also negatively impact post-harvest handling, transportation, and storage

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(Stathers et al., 2013; Mattos et al., 2014). Rising temperatures can diminish the nutritional value of food crops (Da Matta et al., 2013) and lead to extreme heat stress, reducing the productivity and future potential of farm laborers (Watts et al., 2018).

These challenges are creating disruptions in global agricultural production, contributing to supply chain instability and worsening food security. As a result, it is essential to transition toward climate-resilient agriculture. Climate-smart agriculture (CSA) provides a framework to address these challenges by promoting increased productivity, enhanced resilience, and reduced GHG emissions (Kumar and Sidana, 2019). Capacity-building programs that promote CSA help farmers adapt to and mitigate the impacts of climate change. Several factors influence the adoption of CSA practices, including social and economic variables such as education, age, gender, and access to extension services and credit (Deresa et al., 2009). Research shows that education, participation in social groups, and access to credit play significant roles in the adoption of CSA practices (Uddin et al., 2014; Abegunde et al., 2020). Other important factors include farm location, the age of the farmer, and their exposure to climate risks (Ojoko et al., 2017; Akrofi-Atiotianti et al., 2018; Aryal et al., 2018).

Punjab, known for its fertile land and abundant rainfall, has led agricultural productivity since the Green Revolution. Modern farming technologies, such as high-yielding seed varieties, increased use of fertilizers, and enhanced irrigation infrastructure, have driven this growth. However, the sustainability of Punjab's agricultural success is under threat due to environmental degradation, including groundwater depletion and soil fertility loss (Dutta and Dillion, 2020; Nair and Singh, 2016; Pandey et al., 2019). Additionally, climate variability has intensified these challenges, making resource-intensive practices even more unsustainable.

In response to these challenges, many farmers in Punjab have adopted climate-smart practices such as short-duration crop varieties, improved irrigation, direct-seeded rice cultivation, zero-tillage drilling, and laser leveling (Kumar and Sidana, 2018). These practices help farmers adapt to climate change, mitigate its impacts, and achieve food security (Belay et al., 2023; Sahoo and Moharaj, 2022).

CSA, which integrates sustainable production systems with reduced emissions and increased resilience, is key to climate change mitigation and adaptation (Lipper et al., 2014). Empowering farmers through grassroots-level research, extension work, and community involvement is essential for building their capacity to adapt to climate change. The active participation of farmers in decision-making processes is critical to the success of climate change adaptation initiatives (Gardezi and Arbuckle, 2020). This study identifies the key determinants influencing the adoption of CSA practices in Punjab agriculture.

II

MATERIALS AND METHODS

(i) Selection and Description of the study area

Punjab, located in the northwest of India, is known for being one of the country's most fertile states. It spans an area of 50,362 square kilometers, with assured irrigation covering the cultivable land. The state is divided into three agro-climatic zones: the sub-mountainous zone, which accounts for 19 per cent of the total area; the central plain zone, making up 47 per cent; and the southwestern zone, comprising 34 per cent of the state's geographical area.

A multistage sampling technique was used for the sample selection. In the first stage, one district from the sub-mountainous zone (Roopnagar), three from the central plain zone (Sangrur, Patiala, and Fatehgarh sahib), and two from the southwestern zone (Mansa and Sri Muktsar Sahib) were selected based on the percentage distribution of the area under zones in Punjab State (Figure 1). Two villages from each district were chosen from each district randomly in the second stage. Later, at the third stage, a list of farmers adopting various climate-smart practices, i.e., direct seeding of rice, short duration varieties, laser land leveling, baling, use of super seeder, happy seeder, zero till drill in wheat sowing, was prepared for the villages in consultation with KVK (Krishi Vigyan Kendra)scientists and other extension specialists like agriculture development officers. From the list, 20 farmers from each village were selected, comprising both CSA adopters and non-adopters, consisting of a sample of 240 farm households.

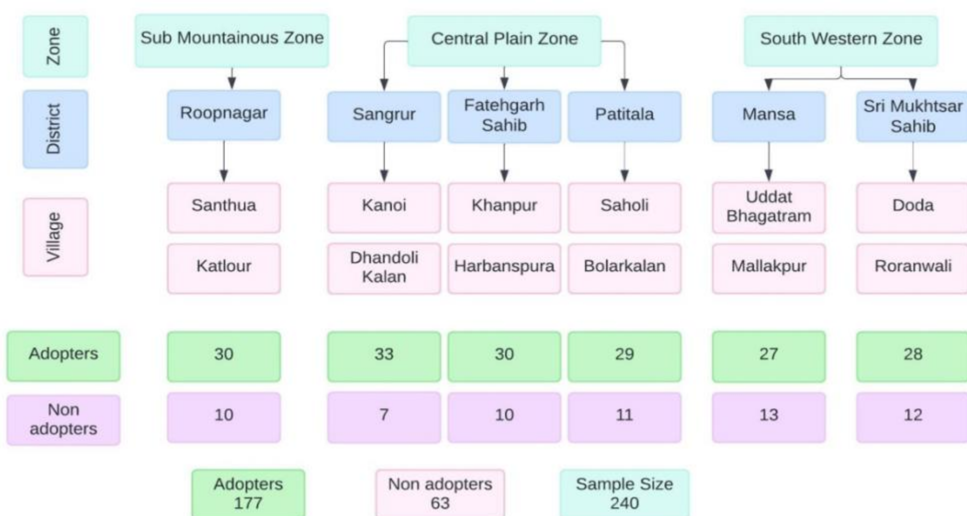

Figure 1. Distribution of Sample Respondents: Adopters and Non-Adopters

Personal interviews were held to collect primary data on a well-structured and pre-tested schedule. The information related to various aspects of a farmer like socio-economic profile, operational holding, source of irrigation, yield, farm inputs (seed, fertilizer, pesticides, diesel), energy for irrigation, human labour, machine labour, and crop residue management practices, food consumption, and expenditure, etc. was collected from selected farmers. The data was collected for various climate-smart agriculture practices (CSAPs) adopted for the agricultural year 2021-22.

The study found that the adopters chose more than one climate-smart practice in their field. The various combinations of CSAPs adopted by sample farmers were identified for farmers following paddy and wheat crops, respectively. There were 177 adopters and 63 non adopters in paddy and wheat crops (Table 1).

TABLE 1. DETAILS OF CLIMATE SMART AGRICULTURE PRACTICES IDENTIFIED BY SAMPLE FARMERS, PUNJAB, 2021-22

S.No. (1)	Climate Smart Agriculture Practices (CSAPs) (2)	Adopters (3)	Per cent (4)
1	LLL	15	8.47
2	SDV	9	5.08
3	DSR	5	2.82
4	DSR+SDV+B+LLL	8	4.52
5	DSR+SDV+B+ZT+LLL	5	2.82
6	DSR+SDV+HS+LLL	10	5.65
7	DSR+SDV+HS+ZT+LLL	7	3.95
8	DSR+SDV+SS+LLL	14	7.91
9	DSR+SDV+ZT+LLL	12	6.78
10	SDV+B+LLL	13	7.34
11	SDV+B+ZT+LLL	18	10.17
12	SDV+HS+LLL	19	10.73
13	SDV+SS+LLL	16	9.04
14	SDV+ZT+LLL	18	10.17
15	SDV+SS+ZT+LLL	8	4.52
	TOTAL	177	100.00

Note: LLL= Laser land leveling, SDV= Short duration varieties, DSR= Direct seeded rice, SS= Super Seeder, HS= Happy Seeder, ZT= Zero Tillage, and B= Baling.

Many of the sample farmers followed multiple practices. So, these have been distributed according to the highest area sown under each climate-smart practice (Table 2). In our study, there were 26.25 per cent of the non-adopters in both paddy and wheat crop. In paddy crop, 47.08 per cent of the adopters were using short-duration varieties followed by laser land leveler (13.75 per cent) and direct seeded rice (12.91 per cent). Meanwhile, in the wheat crop, 24.58 percent have adopted super seeder for sowing, followed by zero tillage (22.50 per cent) and happy seeder (11.67 per cent).

TABLE 2. DISTRIBUTION OF FARMERS AMONG CSA PRACTICES ADOPTED UNDER PADDY AND WHEAT CROP IN PUNJAB, 2021-22

CSA practices adopted in paddy crop			CSA practices adopted in wheat crop		
Technology (1)	Frequency (2)	Percentage (3)	Technology (4)	Frequency (5)	Percentage (6)
Non adopters	63	26.25	Non adopters	63	26.25
	Adopters			Adopters	
SDV	113	47.08	SS	59	24.58
LLL	33	13.75	ZT	54	22.50
DSR	31	12.91	HS	36	15.00
			B	28	11.67
Total	240	100.00	Total	240	100.00

(ii) Extent of Adoption of Climate Smart Agriculture Technologies

Adoption is the choice to fully utilize an innovation as the best course of action. Adoption has been defined as people's willingness to use the advised climate-smart technologies in their industry. The percentage of adopted practices represents the extent of adoption for climate-wise practices. Responses regarding the extent of adopting a list of suggested practices by the implementing agency were obtained. The CSA villages adopted seven technologies. These include direct seeded rice, laser land leveling, short-duration varieties, zero tillage, happy seeder, super seeder, and baling. Farmers' adoption of the CSA non-adopters sample was insignificant and was not used for further analysis. The extent of adoption of climate-smart technologies was calculated by using the formula:

$$\text{Extent of Adoption of CSA technology} = \frac{\text{Technologies being practiced}}{\text{Technologies demonstrated}} \times 100$$

(iii) Composite Index of CSA Technologies

The recommendations of subject matter experts and Principle Component Analysis (PCA) were considered when constructing a composite index. A set of K^{th} components accounting for 100 per cent of the variation across all proposed technology components was considered. In a correlation matrix, where the columns represent Eigen vectors and the rows are variables, the weight (wi) coefficients of technological components, such as, are calculated as follows:

$$W_i = \frac{M_i}{\sum M_i}$$

Where,

W_i = Weight or coefficient of component of technology

M_i = Maximum element in i^{th} row

$\sum M_i$ = Sum of maximum element in i^{th} row

The required linear function for deriving a composite index will be,

$$S_i = W_1X_1 + W_2X_2 + \cdots + W_nX_n$$

Where, S_i is the Composite index score, and X_i's are the Adoption scores for individual CSA technology.

This provides an adoption index of all CSA technologies for each cultivator. The composite index obtained in the process lies between 0 and 1 with the help of the cubic root method. The composite scores of farmers were classified as low level (< 0.51), medium level (0.56- 0.65), and high level (> 0.66) of adoption by using the cumulative cube root method.

(iv) Tobit Model

James Tobin originally developed the Tobit model as an extension of the probit model (Gujarati, 2004). This model, often referred to as a censored regression or limited dependent variable model, incorporates both data at the threshold and above the threshold in its estimation. The Tobit model is frequently applied to examine awareness and adaptation to climate change and to assess the hypothesis related to farm technology adoption. A key aspect of the Tobit model is that it captures both the decision to adopt and the degree of adoption (Tobin, 1958). In its simplest form, the Tobit model is described as follows (Greene, 2003).

$$y_i^* = x_i^* \beta + e_i (1) \qquad y_i = y_{i,}^* \; if \; y_i^* > \gamma (2) \qquad y_i = 0, if \; y_i^* \leq \gamma \qquad (3)$$

where y_i^* is the dependent variable, which is measured using a latent variable y_i for positive values and censored otherwise, β is a vector of estimable parameters, x_i^* is a vector of explanatory variables, $x_i^* \ \beta$ is a product of the vector of parameter and explanatory variable, e_i is a normally and independently distributed error term with zero mean and constant variance σ_2 , and N is the number of observations. Adopted from Carson and Sun (2007), the likelihood function for the model implied by Eqs. (1) and (2) is written as

$$L\ (\alpha, \beta, \sigma) = \prod_{i=1}^{n_0} \emptyset (\frac{\gamma - \alpha - x_{i\beta}}{\sigma}) \ \prod_{i=n_{0+1}}^{n} \frac{1}{\sigma} \emptyset (\frac{y_i - \alpha - x_{i\beta}}{\sigma}) \qquad (4)$$

III

RESULTS AND DISCUSSION

i) Descriptive Statistics

The summary statistics of the variables used in the study have been presented in Table 3. The age of the farmer, a quantitative variable measured in years, has been considered a determinant of the adoption of modern technology, and the mean age is 48.34 years (Tiwari et al., 2008; Aryal et al., 2018; Kumar & Kaur, 2018; Mango et al., 2017; Amadu et al., 2020). The education level of farmers has been considered as another variable and is obtained by the number of years that he has attended school. Education increases his ability to receive, process, and use information relevant to adopting a new technology (Mango et al., 2017; Amadu et al., 2020; Sardar et al., 2020). We also expected a positive association with adopting climate-smart technologies, and the average number of years of education is 9.30. The dependency ratio is the ratio of the number of family members below the age of 15 and above 65 (non-working).

TABLE 3. DESCRIPTION OF THE EXPLANATORY VARIABLES USED IN TOBIT MODEL

Explanatory variables (1)	Description (2)	Mean (3)	Max (4)	Min (5)
Age (years)	Continuous	48.34	72	23
Education (years)	Continuous	9.30	17	0
Dependency ratio	Continuous	0.54	2	0
Operational holding size (ha)	Continuous	5.90	49.29	0.81
Total livestock unit (numbers)	Continuous	5.37	17	0
Trainings and exposure visits (numbers)	Continuous	0.63	3	0
Other qualitative variables		Number		Per cent
Access to non-farm income	Dummy = 1 if the farmer has access to credit;	56		23.33
	0 = otherwise	184		76.67
Mass media exposure	Low=1	169		70.42
	Medium=2	60		25.00
	High=3	11		4.58

The mean dependency ratio in this study is 0.54. Research findings indicate that farm size has both positive and negative impacts on technology adoption, suggesting that the relationship between farm size and adoption is not straightforward (Bradshaw et al., 2004). Vijayasarathy and Ashok (2015) observed that smaller farms might be more inclined to adopt technologies requiring intensive management. This study anticipates either a positive or negative correlation between farm size and adoption, with an average operational holding of 5.90 hectares.

Livestock ownership has been found to positively influence natural resource conservation (Willy and Holm-Müller, 2013). However, Adimassu et al. (2016) noted that the effect of livestock holding on Climate-Smart Agriculture (CSA) practices is inconsistent. This may be because some farmers rely heavily on livestock for their income, reducing their motivation to adopt CSA practices. Training and exposure visits are crucial for building farmers' capacity, increasing interest in adaptation technologies, and enhancing technical abilities (Barrett et al., 2002; Sidibé, 2005). The adoption of CSA measures is expected to be positively related to the number of training sessions attended through extension services and Krishi Vigyan Kendras (KVKs).

Higher income allows farmers to invest in capital-intensive and labor-saving agricultural technologies, which positively impacts the adoption of CSA practices (Huang et al., 2020). Off-farm income, which was available to 23.33 per cent of the farmers in the study, helps farmers overcome financial constraints and increases the likelihood of CSA implementation. Mass media also plays an essential role in quickly disseminating information to farmers, helping them become aware of new technologies. In this study, farmers' exposure to mass media—such as radio, television, printed farm literature, and social media—was categorized into low, medium, and high. Seventy per cent of the farmers were classified as having low exposure to mass media.

ii) Development of Technology Adoption Index for Adoption Of CSA Practices

The overall weighted adoption index for each farmer was calculated using Principal Component Analysis (PCA). PCA is an objective tool that assigns higher weights to technologies that significantly contribute to the variation in the adoption levels of the farmers in the study. The principal components derived from the analysis were utilized to determine the weights. The highest principal component for each technology was selected based on the results, and the ratio of each maximum principal component to the total was used to calculate the actual weight. This weight was then employed to compute each farmer's adoption score. Among the technologies adopted by farmers, laser land leveling received the highest weight of 0.250, followed by short-duration varieties at 0.232. Baling and the happy seeder recorded the lowest weights, at 0.070 and 0.079, respectively (Table 4).

TABLE 4. COMPUTED WEIGHTS FOR CSA TECHNOLOGIES

Sr. No. (1)	CSA Technology (2)	Weights (3)
1	Laser Land Levelling (LLL)	0.250
2	Short Duration Varieties (SDV)	0.232
3	Direct Seeded Rice (DSR)	0.137
4	Zero Tillage (ZT)	0.136
5	Super Seeder (SS)	0.096
6	Happy Seeder (HS)	0.079
7	Baling (B)	0.070

At an overall level, laser land levelling had a maximum weight of 0.250, followed by short-duration varieties, i.e., 0.232. Baling and happy seeder obtained the least weight of 0.070 and 0.079, respectively (Table 4). The technology development index for each sample farm is calculated based on weights obtained for each CSA technology. The technology adoption index ranged from 0 to 1, with 0 indicating no adoption while 1 means adoption of all demonstrated technologies. The category-wise distribution in Figure 2 revealed that the maximum percentage of adoption was observed in the medium adopter category (50.85 per cent), followed by high adopter category (38.98 per cent) and low adopter category (10.17 per cent).

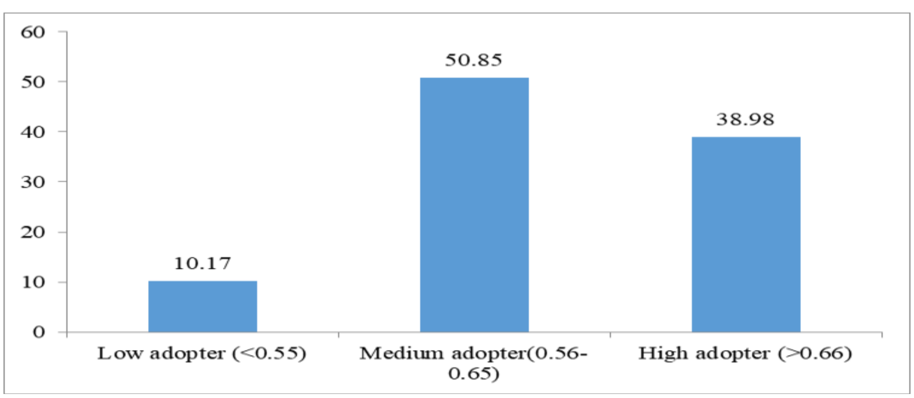

Figure 2. Category Wise Technology Adoption in Punjab

So, to maximize the adoption rate, it is essential to identify the significant factors that facilitate the adoption of CSA practices. Therefore, the Tobit model was used to identify the determinants of adoption.

iii) Factors Affecting the Adoption of Climate Resilient Technologies

The household socio-economic characteristics, operational farm size, number of trainings attended, access to non-farm income, and exposure to mass media were taken into account, and the results of the Tobit model are displayed in Table 5. The likelihood ratio statistics and Wald Chi-square test demonstrated that the explanatory variables collectively influenced the intensity of adoption.

The relationship between age and the adoption of climate-smart agricultural (CSA) practices was found to be significantly negative, indicating that middle-aged farmers were more likely to adopt CSA practices. Education showed a significant and positive effect, playing a crucial role in the adoption of CSA practices. Educated farmers tend to have better access to information and are more capable of evaluating the economic and technical feasibility of conservation measures (Mango et al., 2017). Additionally, training and exposure visits were found to significantly and positively influence adoption intensity (Kumar, 2020). After receiving training on CSA technologies, farmers gained a better understanding of the importance of adopting multiple technologies simultaneously. Access to non-farm income and mass media exposure also had positive and significant effects on the intensity of CSA adoption, as indicated in Table 5.

TABLE 5. FACTORS AFFECTING ADAPTATION DECISION OF CSA PRACTICES: ESTIMATED COEFFICIENTS OF THE TOBIT MODEL

S.No. (1)	Variables (2)	Coefficient (3)	Std. error (4)	p value (5)
1.	Constant	0.44^{**}	0.15	0.003
2.	Age	-0.01^{***}	0.01	0.000
3.	Education	0.02^{**}	0.01	0.017
4.	Dependency ratio	0.01	0.04	0.805
5.	Operational farm size	0.02^{***}	0.01	0.000
6.	Trainings attended	0.13^{***}	0.03	0.000
7.	Total livestock unit	-0.01	0.01	0.600
8.	Access to non-farm income	0.12^{**}	0.04	0.026
9.	Mass media exposure	0.08^{**}	0.04	0.026
Log likelihood	-91.32			
Pseudo R2	0.4084			
LR chi-square	126.08			
p value > chi square	0.4084			

*Note: ***, ** and * denote significance at 1, 5 and 10 per cent levels, respectively* *iv) Complementary or Trade Off Among the Multiple CSA Practices*

Adopting one technology affects the adoption of another technology, implying that there could be complementarities or trade-offs among the adoptions of multiple CSA practices. It is evident from Table 6 that laser land levelling has a positive correlation with all other technologies at a significant level of 1 per cent. Similarly, SDV has a significant positive correlation at 1 per cent. Studies have also mentioned that laser land levelling enhances the yield of the crops, and more than 70 per cent of the farmers in the study had adopted LLL. Farmers were either choosing super seeder or happy seeder for wheat sowing, which showed a negative correlation with each other.

TABLE 6. CORRELATION COEFFICIENTS AMONG THE ADOPTION OF CSA PRACTICES

CSA Practices (1)	LLL (2)	SDV (3)	DSR (4)	SS (5)	ZT (6)	HS (7)	B (8)
LLL	1.000						
SDV	0.8205***	1.000					
DSR	0.3636***	0.2066***	1.000				
SS	0.3598***	0.2602***	0.1414***	1.000			
ZT	0.3906***	0.3613***	0.2762***	-0.0452	1.000		
HS	0.2827***	0.2766***	0.2201***	-0.2614***	-0.0752	1.000	
B	0.3099***	0.2492***	-0.0415	0.0092	-0.0956	-0.1672***	1.000

Note: ***, ** and * denote significance at 1, 5 and 10 per cent levels, respectively

v) Reasons for Climate Change

The sample farmers were asked to specify the reasons to enhance the adoption of new technologies. Their responses were gathered and transformed into scores, subsequently ranked using the Garrett ranking method, presented in Table 7. The findings demonstrated that the leading driver for adopting climate-resilient technologies was the excessive depletion of natural resources. The results revealed that the over-exploitation of natural resources was the prime reason for adopting climate-resilient technologies, followed by more areas under paddy cultivation, as paddy crops are one of the major water-guzzling crops, resulting in groundwater depletion. More use of chemical fertilizer ranked as the fifth reason for adopting climate-smart practices, with Garret's score of 40.29.

vi) Consequences of Climate Change

The effects of climate change are wide-ranging and impact various aspects of life. Data from Table 7 highlights the scope of these consequences. The most significant impact, with the highest average Garrett score of 65.92, is the negative effect on human health. This includes issues such as heat-related illnesses, respiratory problems from air pollution, and the spread of vector-borne diseases. The second-highest ranked consequence is the increase in livestock diseases, with a Garrett score of 62.22. This underscores the vulnerability of livestock to changing climate conditions, making them more prone to infections and diseases. The decline in predatory bird populations, including species like owls, falcons, hawks, and eagles, is identified as the third major consequence of climate change by the sample farmers. The reduction in these populations disrupts ecosystem balance. Climate change is also linked to more frequent and intense natural disasters, such as hurricanes, floods, and droughts, which sample farmers ranked as the fourth major consequence. These disasters have severe impacts on communities, ecosystems, and economies. Shifts in temperature and precipitation patterns can negatively affect crop yields, reducing agricultural productivity. This poses a threat to food security and livelihoods, particularly in agriculture-dependent regions. Additionally, changes in precipitation patterns can lead to decreased availability of clean drinking water, impacting both human populations and ecosystems that depend on consistent water sources.

TABLE 7. DISTRIBUTION OF SAMPLE RESPONDENTS ACCORDING TO THEIR PERCEIVED REASONS AND CONSEQUENCES OF CLIMATE CHANGE IN PUNJAB, 2021-22

S.No. (1)	Particulars (2)	Average Garrett's Score (3)	Rank (4)
	Reasons		
1.	Deforestation	51.27	III
2.	More use of chemical fertilizer	40.29	V
3.	Over exploitation of natural resources	58.92	I
4.	More area under paddy cultivation	55.52	II
5.	More use of fossil fuel	43.50	IV
	Consequences		
1.	Human health affected	65.92	I
2.	Decline in crop yield (i.e., foodgrains and vegetables)	33.92	V
3.	Decreased drinking water availability	27.67	VI
4.	Increase in the number of diseases to livestock	62.22	II
5.	Frequent occurring of natural calamities	53.49	IV
6.	Extinction of predatory birds (i.e., owls, falcons, hawks, eagles, etc.)	56.68	III

vii) Reasons for Adoption of Climate Smart Practices

The sample farmers were asked to articulate the factors that motivated them to adopt climate-smart practices. These specific reasons were carefully collected from the households, and the outcomes are presented in Table 8, utilizing the Garrett score methodology. The most prominent reason for adopting climate-smart technologies, with the highest average Garrett score (45.93), was the elevated expense associated with deepening borewells. This reflects farmers' challenges in maintaining access to groundwater for irrigation, which often involves significant costs for borewell maintenance and deepening. The second reason for adopting CSA practices was the expectation of achieving high crop yields. This indicates that farmers are inclined to embrace technologies that promise enhanced productivity to meet growing demands for agricultural products. Effectively using agricultural inputs, such as fertilizers, pesticides, and water, is critical in achieving optimal crop outcomes. This aspect ranks third in motivating farmers to adopt climate-smart practices, underscoring the need for resource-efficient approaches. Labour scarcity, which ranks fourth, showcases farmers' challenges in accessing sufficient labor for various farming activities. This issue has led farmers to adopt technologies that can help alleviate the dependence on manual labor and improve operational efficiency.

TABLE 8. REASONS FOR ADOPTION OF CLIMATE SMART PRACTICES IN PUNJAB, 2021-22

S.No. (1)	Particulars (2)	Average Garrett's Score (3)	Ranks (4)
1.	High cost of deepening borewell	45.93	I
2.	Expectation of high yield	43.99	II
3.	Labour scarcity	38.33	IV
4.	Effective utilization of inputs	39.30	III

These results emphasize the economic, productivity, and resource management considerations that drive the adoption of climate-resilient technologies among Punjab farmers in the specified period. The prioritization of these factors underscores the significance of addressing challenges related to input costs, labour availability, and yield enhancement in agricultural practices.

IV

CONCLUSIONS AND POLICY IMPLICATIONS

The study concludes that adopting climate-smart agricultural (CSA) practices in Punjab is significantly influenced by various socio-economic factors, including age, education, farm size, training, access to non-farm income, and mass media exposure. Middle-aged farmers with larger farms, higher education levels, and access to training and non-farm income are likelier to adopt CSA practices such as Laser Land Levelling and short-duration varieties. The findings indicate that targeted interventions are necessary to increase awareness and adoption of CSA practices, which are vital for building resilience against climate change in Punjab's agriculture sector. From a policy perspective, the study emphasizes the need to strengthen extension services and farmer education programs to promote CSA adoption. Policymakers should focus on increasing farmer training and exposure to climate-smart technologies, mainly through Krishi Vigyan Kendras (KVKs) and other agricultural extension programs. Additionally, mass media should be utilized more effectively to disseminate information about the benefits of CSA practices. Financial support policies, such as subsidies or low-interest loans for adopting CSA technologies, can also incentivize adoption, particularly among smallholder farmers. Particular attention should be given to marginalized groups, including farmers with smaller landholdings or limited access to education, to ensure equitable access to these technologies. By implementing these policy measures, the agricultural sector in Punjab can improve its sustainability, productivity, and resilience to climate change, ultimately enhancing food security and farmer livelihoods

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