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Assessment of Livelihood Vulnerability and Adoption of Climate Smart Agriculture among the Farmers in Ghaziabad, Uttar Pradesh

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Abstract: Climate change is posing serious risks for human beings and the environment, and it is affecting agriculture and food security around the world. Food security will be impacted by changes in the climate and agricultural production systems, but farmers will bear the burden of these changes first. For most of the years, Uttar Pradesh's agricultural growth has continuously lagged behind the national average. From 2005–06 to 2018–19, the agricultural growth rate increased by 3.0% annually (at constant prices of 2011-12). The paper examined the livelihood vulnerability among the farmers and adoption of climate-smart agriculture. The study is based on a primary survey conducted in Ghaziabad district's four blocks, i.e., Bhojpur, Rajapur, Loni and Murad Nagar. There were 100 responses collected from each block, and a total of 400 responses were collected from the study area. The data has been analyzed using techniques such as the Livelihood Vulnerability Index (LVI), which is a balanced weighted average approach, indexing based on UNDP, and climate-wise agriculture practices based on composite score. The study also used multiple linear regression and the ordered logistic regression model. The areas of Loni and Muradnagar are the most vulnerable, have the least potential for adaptation, and are most exposed to socio-environmental stresses. More people are using cost-effective techniques like mulching and composting. The results imply that adoption of CSA practices is significantly influenced by economic viability.
Keywords:*Agriculture, Climate, CSA, Vulnerability, Ghaziabad*

1.Introduction

Climate change is a major problem for the modern world since it threatens agricultural sustainability, rural population livelihoods, and food security (Praveen and Sharma, 2019).It has been estimated that a 2–3.5 °C increase in temperature will result in a 9–25% drop in India's net agricultural income, with major and cumulative effects, especially for smallholder farmers (Venus et al., 2022). According to the Intergovernmental Panel on Climate Change (IPCC), agricultural systems and other natural and human systems are at serious risk from a 1.5 °C rise in temperature over pre-industrial levels (Porter et al., 2019). Farmers will be the first to suffer the consequences of changes in the climate and agricultural production systems, which will impact food security (Datta and Behera, 2022). Climate change and the agricultural sector are closely related, and their connection is especially important given the growing disparity in global food supply and population (Praveen and Sharma, 2019). Lower agricultural productivity and income are therefore mostly caused by inadequate rainfall and its irregular distribution. Changes in the consistency and intensity of rainfall variability are among the most widespread and possibly disastrous effects of climate change on agriculture (Shumetie&Yismaw, 2018).

India is a tropical country that ranked second in the world for weather-related disasters in 2016 and third in terms of natural disasters, with direct economic losses from natural disasters totalling approximately $79.5 billion between 1998 and 2017 (Shakeri et al., 2021). India's climate change projections show that the country's annual mean temperature will rise by 1.7 to 2.02 °C and 2-4.8 °C by 2030 and 2080, respectively, while precipitation may rise by roughly 1.2 to 2.4% and 3.5 to 11.3%, respectively, with the exception of a few regions (Chaturvedi et al., 2012). Since 1961, the overall amount of food produced by agriculture worldwide has decreased by about 21% due to climate change (Ortiz-Bobea et al., 2021). According to estimates of the effects of climate change on Indian agriculture by 2100, substantial variations in temperature and precipitation are expected to reduce rice and wheat yields by 15 and 22%, respectively (Birthal et al., 2014). A total of 296,438 Indian farmers have committed suicide since 1995, primarily as a result of rising agricultural debt and crop failure and production loss brought on by climate extremes (Carleton 2017). The odds of a cyclone, flood, and drought occurring in a given year have been calculated to be 0.11, 0.19, and 0.37, respectively (Patel et al., 2023). These catastrophic events have damaged the state's development, livelihood resources, infrastructure, food security, livestock, and crops (Patel et al., 2024). This understanding has led to research on climate variability at various geographic scales, from local to regional (Katz and Brown 1992; New et al. 2000; Giorgi 2006; Giorgi et al. 2009; Hansen and Indeje 2004). A number of scholars have investigated the increasing frequency of climate-related hazards and the increased intensity of meteorological phenomena (Trenberth and Owen, 1999; Frich et al., 2002; Dastagir, 2015). According to Kreft et al. (2014) state that India ranks sixth in a list of nations having extreme weather events. The economy of Uttar Pradesh is based primarily on agriculture, with more than 47% of the population depending on it for their livelihood. Most of the time, the state's agricultural growth has fallen below the national average. In the period between 2005–06 and 2018–19, the agricultural growth rate increased by 3.0% annually (at 2011–12 prices). In Uttar Pradesh, the mean maximum temperature and mean temperature showed an increasing tendency, whereas the annual rainfall was shown to be trending negatively. High vulnerability to climate change has also been linked to an increase in the frequency of extreme climatic occurrences (Sehgal et al., 2013; Kumar et al., 2014).

The increasing impact of climate change on biodiversity, water balance, food security, and agricultural productivity has drawn more attention from the global scientific community (Jain et al., 2013). Climate variability in deltaic ecosystems has not yet been extensively studied (Solomon et al., 2007; Nash and Grab, 2010; Neal and Phillips, 2011; Ahmed et al., 2017). Several scientists have tried to use meteorological data to assess climate variability (Mooley and Parthasarathy, 1984; Khaki et al., 2018; Kumar and Jain, 2010). By 2050, agriculture will need to feed nine billion people. Food production must rise by 70–100% to achieve this (Godfray et al., 2010). Food security around the world is being threatened by climate change. Climate-smart agricultural technology and practices have the potential to increase household food security, boost resistance to climate change, support value chain growth, and increase smallholder earnings (Mutenje et al., 2019). The timely and successful implementation of climate-smart agricultural techniques depends on farmers' understanding and attitudes regarding climate change and its related effects (Haq et al., 2021). To comprehend farmers' approaches to mitigating the effects of climate change and production issues, it is crucial to examine a variety of activities since one practice might have a significant impact on others (Sardar et al., 2021). The experience, knowledge, and skills of farmers, as well as their socioeconomic standing, institutional and infrastructure support, and the presence of enabling legislation, all have an impact on their desire to implement CSAPs (Ruben et al., 2021). The two primary goals upon which the paper is based are:To examine the impact of climate-smart agricultural practices on livelihood vulnerability, and to identify climate-smart agricultural practices adopted by farmers and factors influencing the adoption of climate-smart agricultural practices.

2. Study Area

Ghaziabad district is the largest and also the fastest growing district in Uttar Pradesh. The agricultural growth of Ghaziabad makes it one of the most significant districts in Uttar Pradesh. It is situated between latitudes 28°30' and 28°59' North and longitudes 77°26' and 78°10' East. On November 14, 1976, the district of Ghaziabad was established. It has an approximately rectangular shape. It measures 37 kilometres in width and 72 km in length (Fig. 1).

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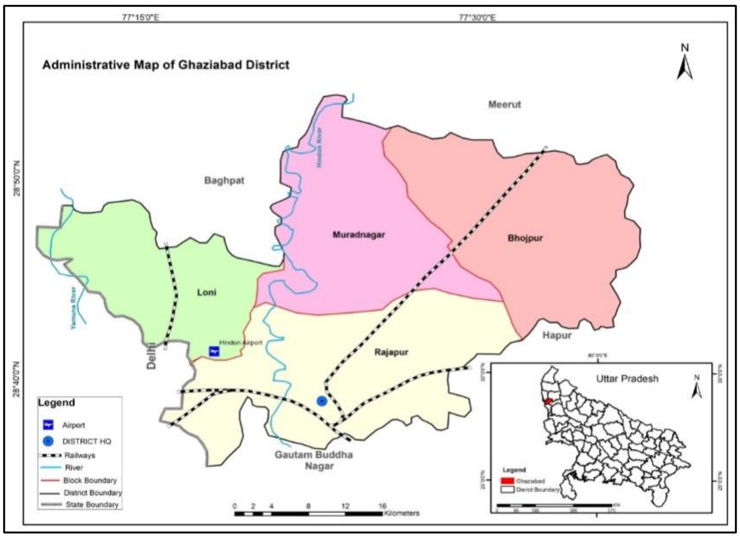

Figure 1: Location of the study area

Uttar Pradesh's Ghaziabad is a sizable suburban district. The third most populous district in Uttar Pradesh, according to the 2011 survey, is Ghaziabad. Ghaziabad is a district located in the centre of the Ganga-Yamuna doab

3. Research Methodology

3.1 Data Source: The study is based on primary survey conducted in Ghaziabad' district's four blocks i.e. Bhojpur, Rajapur, Loni and Muradnagar. There 100 responses from each block and total 400 responses were collected from the study area. Farmer's perception and their observation about adaptation of new technologies were also collected. **Secondary Data:**Thedata isgathered from various sources such as various literatures, reports, agriculture department etc.

3.2 Data Analysis: The present study has used suitable statistical and mathematical techniques, including mean, ratios, percentages, standard deviation, and coefficient of variance, to analyse the data, depending on the type and volume of data available.

3.2.1 Livelihood Vulnerability: Sullivan et al. (2002) describe the Livelihood Vulnerability Index (LVI) as a balanced weighted average technique in which each subcomponent makes an equal contribution to the overall index, despite the fact that each major component is made up of a variable number of sub-components. In the present study, the livelihood vulnerability of the sample of households to climate change was evaluated using the Livelihood susceptibility Index (LVI), which was created by Hahn et al. (2009).

3.2.1.1 Calculation of the LVI

The LVI is composed of eight major elements: livelihood strategies, health, social networks, food, water, housing and natural disasters, climate variability, and sociodemographic profile. Sub-components exist within each major component. A total of 36 sub-components formed these eight primary components (Shah et al., 2013; Aryal et al., 2014). To analyze the index, the following four main steps were followed:

Transforming measurement units,

Standardization of sub-components: Since the subcomponents were measured on various scales, it was first important to standardise each one as an index. The life expectancy index is calculated using equation (1), which was modified from the Human Development Index. It is the ratio of the range of pre-established maximum and minimum life expectancy and the difference between the actual life expectancy and a pre-selected minimum (Mcsweeney et al., 2010).

$$\text{Index } S_d = \frac{S_d - S_{min}}{S_{max} - S_{min}} \quad \ldots\ldots\ldots 1$$

Where,

S_d = The actual value of a subcomponent for farm household

S_{min} = Minimum value for each sub-component were determined using data from all the selected farm households

S_{max} =Maximum value of each sub-component were determined using data from all the selected farm households.

Averaging of sub-components: Each indicator was standardised, and the value of each major component was determined by averaging the sub-components using equation (2).

$$M_d = \frac{\sum_{i=1}^{n} \text{Index } S_{di}}{n} \quad \ldots\ldots\ldots 2$$

Md= Thesociodemographic profile, livelihood strategies, health, social networks, food, water, housing, natural disasters, and climate variability are among the eight main elements of area D.

Index S_{di}=Sub-components, where n is the number of sub-components in each major component and i is the index.

Calculating Final LVI Score: The final LVI score was determined by averaging the data for each of the eight major components using Equation (3). Each major component's value was determined by averaging its sub-components.

$$LVI_d \frac{\sum_{i=1}^{8} W_{mi} M_{di}}{\sum_{i=1}^{8} W_{mi}} \quad \ldots\ldots\ldots 3$$

Expanded From

$$LVI_d = \frac{W_{SDP} S_d + W_{LS} S_d + W_{SN} S_d + W_H S_d + W_F S_d + W_W S_d + W_{HS} S_d + W_{NDCV} S_d}{W_{SDP} + W_{LS} + W_{SN} + W_H + W_F + W_W + W_{HS} + W_{NDCV}} \quad \ldots 4$$

Where,

LVI_d= Livelihood vulnerability index for study block d equals the weightedaverage of the eight major components.

M_{di} = Major component for block indexed by i

W_{mi} = Weight of each major component

3.2.1.2 Climate-Smart Agricultural Practices

Climate-smart farming methods were evaluated on a binary scale, with each method being categorised as either implemented by farmers (1) or not adopted (0). With this method, farmers who had adopted particular CSA practices could be easily distinguished from those that had not.

3.2.1.2.1 The Composite Score

A composite scoring method was used to evaluate farming households' adoption of Climate-Smart Agriculture (CSA) practices (Abegunde et al., 2019). A response of "Yes" (adoption of the practice) was valued 1 on this method's binary scale, whereas a response of "No" (non-adoption) was valued 0. Twelve CSA practices were used to measure the adoption level, and each practice made an equal contribution to the composite score. Respondents were divided into three categories according to their scores: low or non-adopters, who showed little or no adoption; moderate adopters, who showed partial adoption; and high adopters, who indicated significant adoption of CSA techniques.

High adopters = Respondents points fall between 12 and (M + S.D) points.

Moderate adopters = Respondents between upper and lower categories

Low adopters = Respondents whose points fall between (Mean − S.D) and 0

3.2.1.3 Ordered Logistic Regression Model

The association between an ordered multilevel dependent variable and independent variables was modelled using ordinal logistic regression. There is a natural order or ranking to the dependent variable's values in the modelling. They were especially appropriate in cases where the dependent variable denotes rankings or levels, such the degree of adoption of Climate-Smart Agriculture (CSA) methods (low, moderate, high, as an example). Tiwary and Bhowmick (2014) state that the dependent variable Yi is the degree of adoption of CSA techniques (high adopters = 3, moderate adopters = 2, and low adopters = 1). The model of Ordered Logistic Regression has the following general form:

$$\Pr(Y \leq j) = \left(\frac{\sum pr\ (Y \leq j)|X}{1 - \sum pr\ (Y \leq j)|X}\right) = \alpha_j + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots + \beta_{15} X_{15}$$

Where,

Y	=	Dependent variable (level of CSA adoption)
α	=	Threshold
β1- β15	=	Estimated parameters
X1	=	Age of the household head (hhh)
X2		Gender of the household head (hhh)
X3	=	Education status of the household head
X4	=	Farming experience
X5	=	Market distance
X6	=	Access to extension
X7	=	Access to credit
X8	=	Participate in training
X9	=	Member in local area
X10	=	Access to climate change information
X11	=	Family size
X12	=	Adult Cattle Unit (ACU)
X13	=	Off-farm income
X14	=	On-farm income
X15	=	Farmers category

3.2.1.4 Variance Inflation Factor

Multicollinearity testing among the continuous explanatory variables is crucial to ensuring that the Ordered Logistic Regression (OLR) model is appropriate for examining the impact of explanatory factors on Climate-Smart Agriculture (CSA) practices. This was done using the Variance Inflation Factor (VIF) as a diagnostic metric. The VIF measures the degree to which multicollinearity in the model inflates the variance of an estimated regression coefficient (Madhuri et al., 2014). The following formula was used to determine the VIF for each explanatory variable:

$$VIF = \frac{1}{1 - R^2}$$

Where,

R^2 = The coefficient of determination (Xi) is the result of regressing the variable of interest on each of the other explanatory factors in the model.

If there is no collinearity among the regressors, the VIF value is 1. A variable is deemed to be very collinear when its VIF value is greater than 10, which occurs when its R2 value is greater than 0.90 (Gujarati, 2004).

3.1.2.5 Contingency Coefficient (CC)

A contingency coefficient is calculated to ascertain the level of connection between the dummy explanatory variables. According to Madhuri et al. (2014), a score of CC > 1 indicates a greater correlation between the two variables. The following is how the contingency coefficient (CC) was calculated:

$$CC = \sqrt{\frac{x^2}{x^2+N}}$$

Where,
CC = Coefficientofcontingency
X^2 = Chi-square test
N = Totalsamplesize

3.1.2.6 Impact of climate-smart agricultural practices on livelihood vulnerability

Multiple linear regression was used to examine the impact of climate-smart agricultural practices on livelihood vulnerability of the sample households.

Multiple linear regression

According to Tiwary and Bhowmick (2014), the response variable was the farmers' Livelihood Vulnerability Index (LVI), while the explanatory variables were climate-smart agricultural practices, access to climate change information, and training on CSA methods. This is how the multiple linear regression model is explained:

$$Y = \alpha_0 + \alpha_{1X_1} + \alpha_{2X_2} + \alpha_{3X_3} + \mu$$

Where,

Y = Livelihood VulnerabilityIndex

α_0 = Intercept

α1-α3 = Coefficients for the explanatory variables

μ = Error term

X1 = Climatesmartagri cultural practices

X2 = Access to informationonc limatechange

X3 = Access to training on CSApractices

Result and Discussion

4. Livelihood vulnerability in Ghaziabad

The Livelihood Vulnerability Index (LVI) for the four Ghaziabad blocks of Bhojpur, Rajapur, Loni, and Murad Nagar is analyzed in the following table 1. Loni has significant vulnerabilities, as seen by the greatest average family size (0.478) and the highest percentage of illiterate household heads (0.448), indicating to potential challenges with resource management and education. Murad Nagar is mainly dependent on agriculture for its livelihood (46.5% of households), which makes it vulnerable to changes brought on by the climate. The data on natural disasters, which show that Murad Nagar has the highest mean standard deviation for both

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maximum daily temperature (0.118°C) and precipitation (0.175 mm), as well as the highest percentage of homes impacted by flooding (53.4%), further confirm this. Rajapur also has issues with health access; on average, it takes 0.517 minutes to get to a district health facility, and a large portion of families (54.1%) say there are no health services available. Together, the data show that every block has different vulnerabilities, with Murad Nagar being particularly vulnerable to livelihood-based and climate-related threats.

Table 1: Indexing value of sub- components of Livelihood Vulnerability index for the study area

Major components	Sub components	Units	Bhojpur	Rajapur	Loni	Murad Nagar
Socio-demographic	Dependency ratio	Ratio	0.037	0.031	0.032	0.037
	Female-headed households	Per cent	0.168	0.189	0.218	0.101
	Average age of head of household	Years	0.497	0.521	0.487	0.521
	Per cent of illiterate household heads	Per cent	0.147	0.147	0.448	0.251
	Average family size	Count	0.27	0.25	0.478	0.287
	Average years of farming experience	Count	0.508	0.55	0.487	0..298
Livelihood strategies	Households with family members working in a different community	Per cent	0.624	0.69	0.665	0.568
	Households dependent solely on agriculture as a source of income	Per cent	0.376	0.31	0.354	0.465
	Average livelihood diversification index (Herfindhal Index)	Index	0.49	0.48	0.52	0.451
Social Network	Average receive: give (ratio)	Ratio	0.294	0.278	0.298	0.461
	Average borrow: lend money (ratio)	Ratio	0.42	0.46	0.45	0.456
	Households that have received local government assistance in the past one year (during flood season)	Per cent	0.333	0.356	0.37	0.451
	HH does not have any extension contact	Per cent	0.291	0.334	0.332	0.478
Health	Average time to district health facility (minutes)	Minutes	0.18	0.517	0.235	0.256
	Average distance to district hospital	Km	0.12	0.351	0.16	0.16
	HH reporting non availability of health facilities in nearest PHC	Per cent	0.43	0.541	0.418	0.48
	Households with family members with chronic illness	Per cent	0.457	0.51	0.419	0.478

Food	Households that do not save crops	Per cent	0.645	0.561	0.67	0.487
	Households that do not save seeds	Per cent	0.512	0.578	0.73	0.561
	Average Crop Diversification index (Herfindahl Index)	Index	0.27	0.32	0.31	0.11
	Average Livestock Diversity Index	Index	0.36	0.37	0.39	0.251
Water	Utilize natural source of water	Per cent	0.435	0.51	0.521	0.834
	Households reporting recent drying of water sources	Per cent	0.434	0.412	0.452	0.471
	Households that do not have a consistent water supply for drinking	Per cent	0.536	0.421	0.454	0.58
	Households reporting water conflicts	Per cent	0.512	0.523	0.567	0.669
	Households reporting shortage of water supply for farming	Per cent	0.524	0.566	0.589	0.718
	Households storing water	Per cent	0.678	0.588	0.59	0.73
	Average time to water source	Minutes	0.356	0.478	0.389	0.34
	Inverse of the average amount (liters) of water stored per household	1/# Litre	0.39	0.48	0.36	0.32
House	Households whose houses do not have a solid structure and are prone to damage by floods	Per cent	0.364	0.356	0.471	0.512
	Flood affected households	Per cent	0.334	0.29	0.323	0.534
Natural disasters & climate variability	Households who were not provided with early flood warnings	Per cent	0.512	0.51	0.567	0.523
	Households experienced catastrophic accidents or deaths from floods in the past five years	Per cent	0.212	0.251	0.275	0.334
	Mean standard deviation of the monthly average of average maximum daily temperature (1981-2022)	Celcius	0.078	0.078	0.079	0.118
	Mean standard deviation of the monthly average of the average minimum daily temperature (1981-2022)	Celcius	0.056	0.056	0.056	0.121
	Mean standard deviation of monthly average precipitation (1981-2022)	Millimeter	0.135	0.134	0.123	0.175

Source: Calculated by Author based on Data collected by Primary Survey in 2024

4.1Livelihood vulnerability Indexing value of Major Components

Murad Nagar is the most vulnerable of the four blocks, with the greatest overall Livelihood

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Vulnerability Index (LVI) of 0.420, shown in the table 2. Its unusually high ratings in Water (0.637), House (0.534), and Social Network (0.430) are the main causes of this high vulnerability. Bhojpur, on the other hand, is the least vulnerable, with the lowest total LVI of 0.365. All communities exhibit some level of vulnerability, although Rajapur is most weak in the Health component (0.479), while Loni gets the highest ratings in Food (0.524) and Livelihood methods (0.511). The information shows that vulnerability is influenced by various local circumstances rather than being consistent across communities.

Table 2: Indexed value of major components and overall LVI in Ghaziabad

Components	Bhojpur	Rajapur	Loni	Murad Nagar
Socio-demographic	0.267	0.289	0.275	0.291
Livelihood strategies	0.494	0.491	0.511	0.499
Social Network	0.334	0.356	0.368	0.43
Health	0.297	0.479	0.316	0.345
Food	0.47	0.456	0.524	0.35
Water	0.5	0.469	0.517	0.637
House	0.364	0.321	0.398	0.534
Natural disasters & climate variability	0.201	0.204	0.22	0.256
Overall	0.365	0.382	0.389	0.42

Source: Calculated by Author based on Data collected by Primary Survey in 2024

The Livelihood Vulnerability Index (LVI) for the four blocks of Bhojpur, Rajapur, Loni, and Murad Nagar is shown in the following figure 2. In addition to an overall LVI score, the octagon makes it possible to compare vulnerability across eight key components: sociodemographic, livelihood strategies, social networks, health, food, water, housing, and natural catastrophes & climatic variability.

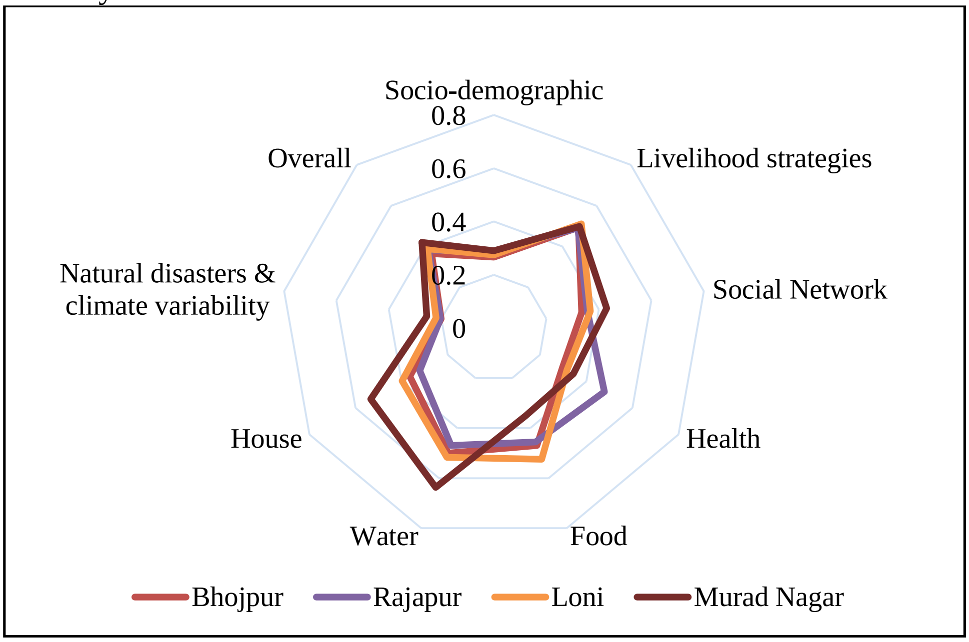

Figure 2: Livelihood vulnerability Indexing value of Major Components

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Since its line covers the largest area, the octagon makes it evident that Murad Nagar is the most susceptible block, especially given its high Water and House ratings. With the smallest enclosed area, Bhojpur, on the other hand, seems to be the least vulnerable overall. The octagon also identifies particular weaknesses for other communities, such as Rajapur's high health score and Loni's high livelihood plans and food scores, showing that every village has a different combination of issues that add to its total susceptibility.

5. Climate Smart Agriculture

A major idea in current agricultural development, climate-smart agricultural practices seek to accomplish three goals at once: increase farmer resilience (adaptation); decrease or mitigate greenhouse gas emissions; and sustainably intensify agriculture for improved livelihoods (Lipper et al., 2014; Bhatnagar et al., 2024).

5.1 Category of adopters of CSA practices in the study area

Climate-Smart Agriculture (CSA) adoption rates among 400 respondents are summarised in the table 3. As the largest group with 157 members, or 39.25% of the total, the data shows that a significant portion of the population belongs to the low adopters category. Additionally, a sizable portion of farmers—124 people, or 31%—are moderate adopters. High adopters comprise the smallest group, including 119 individuals, or 29.75% of the sample as a whole. Overall, the results indicate that most farmers in the research region have either low or moderate adoption rates of CSA practices, suggesting that interventions may be necessary to promote their use.

Table 3: Category of adopters of CSA practices in the study area

Sr. No.	Category of adopters	Frequency	Percentage
1	Low adopters	157	39.25
2	Moderate adopters	124	31
3	High adopters	119	29.75
	Total	**400**	**100.00%**

Source: Calculated by Author based on Data collected by Primary Survey in 2024

5.2 Adoption level of various climate-smart agricultural practices

The study shows that although some farmers are adopting specific CSA practices, a sizable section of the agricultural people has not yet fully applied these practices, especially those are relating to livestock. The following table 4 data shows a distinct hierarchy in the adoption levels of several climate-smart agricultural (CSA) techniques, with the majority of these practices having relatively low to moderate adoption, even though some farmers gave them high ratings. With weighted mean scores of 1.85, fruit-based agroforestry and the use of compost and farmyard manure (FYM) came in first and second, respectively. This suggests that these CSA practices are the most popular among the farmers polled and that their general adoption level is slightly greater than average. On the other hand, micro irrigation and animal nutrition modification had the lowest adoption rates, ranking last on the list with weighted mean scores of 1.62 and 1.63, respectively. With weighted mean ratings ranging from 1.70 to 1.84, most of the practices—such as mulching, minimum/zero tillage, and enhanced crop varieties—were ranked in the middle, indicating a need for better knowledge of their advantages and more widespread use.

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Table 4: Adoption level of various climate-smart agricultural practices

CSA practices	High adoption (3)		Moderate adoption (2)		Low adoption (1)		Total weighted score	Weighted mean score	Rank
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage			
Mulching	115	28.75	100	25	185	46.25	796	1.84	**II**
Minimum/Zero Tillage	111	27.75	54	13.5	235	58.75	733	1.7	**VIII**
Fruit Based Agroforestry	114	28.5	103	25.75	183	45.75	799	1.85	**I**
Integrating Crop Livestock Production	111	27.75	103	25.75	186	46.5	789	1.83	**III**
Micro Irrigation	103	25.75	30	7.5	267	66.75	698	1.62	**X**
Change of Planting Time (before/after onset of rainfall)	109	27.25	98	24.5	193	48.25	775	1.79	**V**
Improved Crop Varieties	118	29.5	61	15.25	221	55.25	749	1.73	**VI**
Diet Improvement for Animals	98	24.5	53	13.25	249	62.25	706	1.63	**IX**
Crop Insurance	110	27.5	68	17	222	55.5	745	1.72	**VII**
Soil Test	103	25.75	72	18	225	56.25	742	1.72	**VII**
Use of Compost & FYM	114	28.5	108	27	178	44.5	798	1.85	**I**
ICT Based Weather Forecast	112	28	90	22.5	198	49.5	780	1.81	**IV**

Source: Calculated by Author based on Data collected by Primary Survey in 2024

5.3 Factors Influencing Climate smart agriculture

The variables related to the implementation of climate-smart agricultural (CSA) methods are shown in this table 5. The dependent variables reveal how many CSA techniques have been adopted; the highest adoption rates are for "Use of Compost & FYM" (Mean = 0.87) and "Integrating Crop Livestock Production" (Mean = 0.83), while the lowest adoption rates are for "Micro Irrigation" (Mean = 0.37). The percentage of farmers who adopted a certain method is probably represented by the mean values for these dependent variables (for example, 87% of farmers utilise compost/FYM). The potential determinants of these adoption choices are known as independent variables, and they are divided into sociodemographic, institutional, sociocultural, climatic, and economic categories. With 25 years of agricultural experience, the average farmer in the sample is a male household head (Gender mean = 0.85, probably an insignificant variable where 1=male) who is approximately 57 years old. Farmers earn a wide variety of incomes; the mean income from farming (Mean = 725,801) is substantially larger than the mean income from off-farming (Mean = 211,227). The characteristics of the sample population and their first exposure to different CSA practices are fundamentally understood by these statistics, which also offer an examination of the ways in which the independent variables affect the adoption of the dependent variables.

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Table 5: Descriptive Statistics: Factors influencing the adoption of climate-smart agricultural practices

Variables	Mean	Std. Dev.
Dependent variables		
Mulching	0.71	0.387
Minimum/Zero Tillage	0.51	0.385
Fruit Based Agroforestry	81	0.382
Integrating Crop Livestock Production	0.83	0.385
Micro Irrigation	0.37	0.49
Change of Planting Time (before/after onset of rainfall)	0.71	0.457
Improved Crop Varieties	0.54	0.5
Diet Improvement for Animals	0.52	0.5
Crop Insurance	0.51	0.5
Soil Test	0.54	0.5
Use of Compost & FYM	0.87	0.35
ICT Based Weather Forecast	0.59	0.495
Independent variables		
Socio-demographic factors		
Age of the household head	57.19	9.241
Gender of the household head	0.85	0.369
Education status of the household head	2.35	1.541
Farming experience	24.98	10.123
Institutional factors		
Market distance	11.99	5.898

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Access to extension functionaries	0.6	0.495
Access to credit	0.67	0.476
Participate in training	0.61	0.495
Socio-cultural factor		
Member in local area	0.54	0.501
Climatic factor		
Access to climate change information	0.57	0.498
Economic factors		
Family size	5.41	0.656
Adult Cattle Unit	2.37	1.5784
Off-farm income	211227	188122
On-farm income	725801	366661
Farmers category	1.68	0.787

Source: Calculated by Author based on Data collected by Primary Survey in 2024

5.2 Factors influencing the adoption of climate-smart agricultural practices

The adoption of climate-smart agricultural methods is greatly influenced by a number of factors, as shown in the table 6. The analysis, is based on a regression model, shows that the adoption of these practices is statistically significantly correlated with education (p=0.021), farming experience (p=0.049), access to extension services (p=0.000), access to credit (p=0.000), training participation (p=0.026), membership in a local area group (p=0.023), access to climate change information (p=0.000), on-farm income (p=0.000), and farmer's category (p=0.027). Adoption is favorably impacted by education, farming experience, and on-farm income, indicating that farmers are more likely to embrace climate-smart practices if they have more education, more experience, and higher on-farm revenue. Similarly, adoption is strongly and favourably predicted by institutional support, such as access to extension professionals, credit, and training, as well as by community involvement (belonging to a local organisation) and climate change awareness. The adoption of these methods, on the other hand, seems to be negatively impacted by belonging to a higher farmer group, which is probably a measure of wealth or land size. It was discovered that the adoption of climate-smart agricultural methods was not statistically impacted by factors such as age, gender, market distance, family size, adult cattle unit, and off-farm income.

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Table 6: Factors influencing the adoption of climate-smart agricultural practices

Variables	Odds ratio	Standard error	Z	P>|z|	95 % confidence interval	
					Lower bound	Upper bound
Socio-demographic factors						
Age (X1)	-0.021	0.023	-0.84	0.415	-0.067	0.028
Gender (X2)	0.078	0.327	0.24	0.812	-0.563	0.708
Education (X3)	0.249	0.117	2.34**	0.021	0.039	0.449
Farming experience (X4)	0.048	0.024	1.99**	0.049	0.001	0.089
Institutional factors						
Market distance (X5)	-0.028	0.021	-0.88	0.375	-0.058	0.032
Access to extension functionaries (X6)	1.117	0.265	4.35***	0	0.608	1.617
Access to credit (X7)	1.049	0.28	3.82***	0	0.49	1.603
Participate in training (X8)	0.613	0.27	2.39**	0.026	0.104	1.102
Socio-cultural factor						
Member in local area (X9)	0.55	0.24	2.27**	0.023	0.081	1.019
Climatic factor						
Access to climate change information (X10)	2.502	0.313	8.24***	0	1.897	3.056
Economic factors						

Family size (X11)	-0.003	0.097	-0.051	0.943	-0.169	0.17
Adult Cattle Unit (X12)	0.199	0.102	1.75	0.08	-0.012	0.414
Off-farm income (X13)	6.03E-07	6.83E-07	0.88	0.377	-7.35E-07	1.94E-06
On-farm income(X14)	3.64E-06	9.70E-07	3.76^{***}	0	1.74E-06	5.54E-06
Farmers category (X15)	-0.803	0.342	-2.390^{**}	0.027	-1.491	-0.159
/cut1	4.721804	1.28812		2.19713	7.24648	(Ancillary parameters)
/cut2	7.726302	1.33813		5.10363	10.349	
Number of observations	400					
LR chi2(15)	402.12					
Prob> chi2	0					
Pseudo R2	0.4569					
Log likelihood	-254.74074					

Source: Calculated by Author based on Data collected by Primary Survey in 2024

6. Impact of climate-smart agricultural practices on livelihood vulnerability

A regression analysis of the effects of several factors on the Livelihood Vulnerability Index (Y) is shown in Table 7. With three independent variables (X1, X2, and X3) plus a constant, the model seems to be statistically significant, as shown by a Prob> F value of 0. This implies that the entire model fits the data well. According to the R2 and Adjusted R2 values of 0.1647 and 0.1578, respectively, the independent variables account for around 16% of the variation in the Livelihood Vulnerability Index. The findings show that livelihood vulnerability is negatively impacted by all three independent variables, as indicated by their small P-values (all less than 0.05) and negative coefficients: climate smart agricultural practices (X1), access to climate change information (X2), and access to training on CSA practices (X3). This suggests that among the sample homes, a decrease in livelihood vulnerability is related to an increase in either of these parameters. Among the factors studied, access to climate change information (X2) shows the strongest correlation, with the largest negative coefficient (-0.01401), indicating that it has the greatest impact on lowering vulnerability.

Table 7: Impact of climate-smart agricultural practices on livelihood vulnerability of the sample households

Livelihood Vulnerability Index (Y)	Coefficient	Std. Error	t	P>|t|
Constant	0.171598	0.005784	30.04	0
Climate smart agricultural practices(X1)	-0.0035	0.000995	-3.39	0.001*
Access to information on climate change (X2)	-0.01401	0.00461	-2.89	0.004*
Access to training on CSA practices (X3)	-0.01384	0.006139	-2.25	0.025*
F value	0.1645			
Prob> F	0			
R_2	0.1647			
Adjusted R_2	0.1578			

Source: Calculated by Author based on Data collected by Primary Survey in 2024

7. Conclusion

The composite LVI showed that the blocks' levels of vulnerability varied significantly. The most vulnerable block was Murad Nagar, with an LVI of 0.420, followed by Loni (0.389). More vulnerability was observed in blocks in the high vulnerability zone, especially in key areas like health, social networks, sociodemographic characteristics, natural catastrophe susceptibility, and serious water availability issues. Based on an intricate relationship between exposure, sensitivity, and adaptive capability, these outcomes emphasise the different levels of susceptibility. The study found that there was variation in the rates of CSA practice adoption, with cost-effective measures like mulching (72.90%) and composting and FYM (85.90%) showing higher adoption rates. It is advised that farmers use mulching techniques appropriate for their particular conditions in order to increase agricultural production and guarantee long-term food security. Sand, plastic film, and crop straw are examples of mulching materials that help control soil temperature, preserve soil moisture, and lessen erosion. By establishing favorable soil conditions, these techniques enhance soil microbiology and plant growth.

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