



Adoption of Climate-Smart Agriculture (CSA) in Flood-Affected Regions of Darbhanga

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HIGHLIGHTS

- Knowledge and income strongly predict CSA adoption; informed, economically secure farmers adopt more climate-resilient practices.
- CSA adoption was uneven; crop production sees higher uptake than smart water and energy interventions.
- Regression explains 50 per cent adoption variance; education, family size, and extension contact significantly influence adoption in flood-prone areas.

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ABSTRACT

The study aimed to evaluate the extent of adoption of Climate Smart Agriculture (CSA) practices among farmers residing in flood-prone areas of Darbhanga, Bihar, and to identify the key socio-economic factors influencing adoption. Data were collected during 2024–2025 from 160 respondents randomly selected from sixteen villages across four flood-affected blocks. A pre-tested interview schedule encompassing five CSA components was employed to gather information on adoption levels and socio-economic characteristics. The adoption of CSA practices was predominantly partial and practice-specific. Crop production practices recorded mean adoption rate of 49.51 per cent, whereas smart water management at 38.37 per cent. Overall, 64.16 per cent of the respondents exhibited a moderate adoption level. Correlation analysis demonstrated significant positive associations between adoption and variables such as knowledge, income, education, and family size. Further, the regression model ($R^2 = 0.500$; $F = 13.451$; $p < 0.01$) identified knowledge, income, education, family size, and extension contact as significant predictors of CSA adoption. The study concluded that improving farmers' knowledge and enhancing their economic capacity could substantially increase CSA adoption, thereby strengthening climate resilience. These results underscore the importance of targeted extension services and capacity-building programs tailored to vulnerable regions.

INTRODUCTION

India's agriculture is mostly rain-fed and extremely vulnerable to natural disasters like droughts and floods, especially in eastern states like Bihar. Flooding regularly affects the Darbhanga district in northern Bihar, upsetting farming practices, livelihoods, and food security. The implementation of Climate Smart Agriculture (CSA) techniques is essential in these delicate agro-ecological zones (Shitu

et al., (2018). According to the Food and Agriculture Organization (FAO), CSA aims to accomplish national food security and development objectives while also improving resilience (adaptation), lowering greenhouse gas emissions (mitigation), and sustainably increasing productivity. Stress-tolerant crop varieties, resource-conserving technologies, enhanced water harvesting, integrated nutrient management, and early warning systems are some of the practices covered by CSA.

India is the nation most affected by flooding after Bangladesh. One-eighth of the country's land area, or about 40 million hectares, is vulnerable to flooding. On average, 14,52,904 homes are damaged, 1793 people are killed, 85,599 cattle are killed, and 7.35 million hectares of land are impacted annually. Floods cause an average of 575 million US dollars in total losses (Dutta & Watts, 2010). Of India's 104.1 million inhabitants, 88.7 per cent live in rural areas, making Bihar the state most vulnerable to flooding. 79.11 million people, or nearly 76 per cent of the population, live in Bihar where flooding is a constant threat. According to WRD (2015), more than 73 per cent of Bihar's land area is designated as a flood-affected region. The main cause of floods in north Bihar is the high water flow brought about by the Himalayan river ranges, which include the Kosi, Gandak, Burhi Gandak, Bagmati, Kamla Balan, Mahananda, and Adhwara. These rivers originate in Nepal. North Bihar invariably floods as a result of these rivers' high discharge and heavy sediment load during the rainy season. Saharsa, Khagaria, Gopalganj, Katihar, Darbhanga, Madhubani, Supaul, East Champaran, West Champaran, Begusarai, and other districts that are within the catchment area of these rivers are the districts in Bihar that have been most severely affected by flooding. North Bihar has experienced the most floods over the past 30 years, and the overall area impacted by floods in Bihar has increased. One of the districts in North Bihar that is particularly impacted by the yearly flood is Darbhanga. Over 90 per cent of the 3.93 million people who live in the Darbhanga district reside in rural areas (DHSD, 2012). The Himalayan river range causes the most flooding in the district in Biraul, Kusheshwar Asthan (East and West), Ghanshayampur, Singhwara, Keoti, and Jale. Usually lasting three to five months at a time, the flooding has a significant negative impact on human life and living conditions, particularly in the marginalized communities.

In Bihar, the National Innovations on Climate Resilient Agriculture (NICRA) program has been instrumental in promoting CSA practices. However, the extent of adoption and the factors influencing it, particularly in flood-prone areas like Darbhanga, require further investigation. Understanding these determinants is essential for designing effective interventions and policies that enhance the resilience of farming communities (Maya et al., 2025; Koyu et al., 2021). Despite policy initiatives and pilot programs promoting CSA, actual adoption among smallholder farmers in vulnerable regions remains limited and uneven. The purpose of this paper is to highlight the various factors influencing the adoption of CSA practices, including socio-economic variables, access to information, and institutional support. For instance, research in the Bundelkhand region highlighted that variables such as education level, income, farm size, access to extension services, and awareness significantly influence the likelihood of adopting climate-resilient technologies.

METHODOLOGY

The state of Bihar is composed of 38 districts, of which Darbhanga was purposively selected for the present study due to its frequent exposure to seasonal flooding and its prominence in flood-prone agro-ecological zones. According to the Bihar State Disaster Management Authority (2022), Darbhanga is one of the

top five districts in the state in terms of flood frequency and agricultural damage caused by climate-induced disasters. For investigation during 2024-25, Hanuman Nagar, Singhwara, Jale and Kusheshwar Asthan blocks of Darbhanga district were selected purposively based on their history of flood vulnerability, agricultural activity, and accessibility. From each block, four villages with notable agricultural activity and prior exposure to Climate Smart Agriculture (CSA) initiatives under NICRA or Krishi Vigyan Kendra (KVK) were purposively chosen, resulting in a total of sixteen villages. A complete household listing of all farming families in each selected village was conducted. From this list, a total of 160 respondents were randomly selected using proportionate random sampling. Primary data were collected through a pre-tested and structured interview schedule administered via personal interviews. The schedule was designed to collect information on socio-economic characteristics, awareness, and adoption of various CSA practices. It consisted of items related to major CSA interventions such as the use of stress-tolerant seeds, raised bed planting, organic inputs, integrated pest management, and water harvesting techniques. Respondents were asked to indicate their level of adoption for each practice using a 3-point Likert scale: fully adopted (2), partially adopted (1), and not adopted (0). The maximum attainable adoption score across all practices was 25.

An adoption Index was calculated for each respondent using the formula:

$$\text{Adoption index} = \frac{\text{Total score achieved}}{\text{Total achievable score}} \times 100$$

To assess the determinants of CSA adoption, data were analysed using multiple linear regression analysis. The dependent variable was the total adoption score of CSA practices. Independent variables included both socio-economic and psychological factors. Statistical analysis was carried out using SPSS 27.0 software. The strength and direction of influence of each predictor variable were examined through regression coefficients and significance values ($p < 0.05$). Multicollinearity diagnostics and model fit statistics such as R^2 and Adjusted R^2 were also evaluated to ensure robustness of the model.

RESULTS

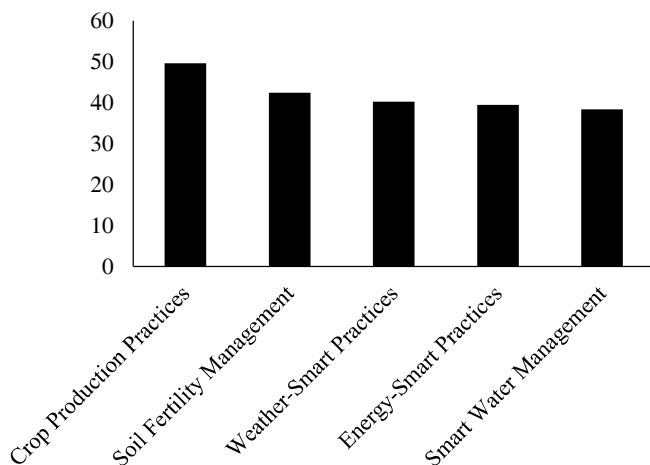
Table 1 presents the weighted mean adoption scores for these CSA components among farmers affected by floods in Darbhanga. Crop production practices had the highest mean adoption rate of 49.51 per cent, largely due to the extensive use of flood-tolerant varieties and intercropping methods (Figure 1). Soil fertility management followed with a mean adoption of 42.33 per cent, reflecting widespread legume rotation practices in the area. Weather-smart and energy-smart practices showed moderate adoption rates of 40.20 per cent and 39.37 per cent, respectively, demonstrating some use of crop insurance and minimum-tillage, although uptake of forecasting tools and renewable energy remained limited. Smart water management recorded the lowest adoption score at 38.37 per cent, indicating ongoing difficulties in adopting technologies like fertigation and water harvesting systems.

The relationship between selected socio-personal, economic, and psychological characteristics of respondents and their adoption

Table 1. Specific Climate-Smart Agriculture (CSA) practices in Flood-affected regions

CSA Component	Mean Adoption (%)	Rank
Crop Production Practices	49.51	1
Soil Fertility Management	42.33	2
Weather-Smart Practices	40.20	3
Energy-Smart Practices	39.37	4
Smart Water Management	38.37	5

(Scores based on 2 = fully adopted, 1 = partially adopted, 0 = not adopted, averaged across practices)

**Figure 1.** Weighted Mean Adoption Scores of Climate-Smart Agriculture

level of Climate Smart Agriculture (CSA) technologies was examined using Pearson's correlation analysis. The results, presented in Table 2, showed that knowledge of CSA practices was the most significant factor positively correlated with adoption ($r = 0.558$, $p < 0.01$), indicating that farmers with greater knowledge were more likely to adopt CSA practices. Income also demonstrated a significant positive correlation ($r = 0.322$, $p < 0.01$), suggesting that economically better-off farmers possessed greater capacity and willingness to invest in CSA interventions, likely due to enhanced access to resources and inputs. Education exhibited a moderate positive correlation ($r = 0.174$, $p < 0.05$), implying that more

Table 2. Association of profile characteristics of respondents and adoption of CSA technologies in flood-prone area

Variables (Unit)	Adoption value of 'r'
Age	-0.002
Marital	-0.055
Family type	0.124
Family size	0.194*
Education	0.174*
Landholding	0.120
Income	0.322**
Extension contact	0.129
Scientific Orientation	-0.051
Attitude	0.015
Knowledge	0.558**

* - Significant at 5 % level of probability, ** - Significant at 1 % level of probability

educated farmers were more receptive to adopting climate-resilient innovations. Family size also showed a positive and significant correlation ($r = 0.194$, $p < 0.05$), reflecting increased labour availability within larger households, which facilitated better management and implementation of CSA practices. Other variables, including age ($r = -0.002$), marital status ($r = -0.055$), landholding size ($r = 0.120$), extension contact ($r = 0.129$), scientific orientation ($r = -0.051$), attitude ($r = 0.015$), and family type ($r = 0.124$), did not exhibit statistically significant associations with adoption levels. Although extension contact and landholding showed weak positive trends, these were not significant at the 5% level, indicating that additional mediating factors might affect their influence on adoption. These findings highlighted knowledge and economic capacity as primary drivers of CSA adoption among smallholder farmers in flood-prone areas, while education and family labour availability provided supportive roles. The results also suggested that institutional support mechanisms, such as extension services and training, require further strengthening to exert a statistically meaningful impact on adoption behaviour.

Table 3 showed that the regression model was statistically significant ($F = 13.451$; $p \leq 0.01$) with a coefficient of determination (R^2) of 0.500, indicating that approximately 50% of the variation in CSA adoption among farmers was explained by the eleven independent variables included in the model. Among the predictors, knowledge emerged as the most influential variable, with a highly significant positive coefficient ($B = 0.503$, $t = 9.623$, $p \leq 0.01$), suggesting that farmers with higher levels of knowledge were more likely to adopt CSA practices. This result aligned with the correlation analysis and underscored the importance of information and awareness in adoption behaviour. Income also exhibited a significant positive effect ($B = 0.101$, $t = 4.051$, $p \leq 0.01$), indicating that farmers with higher income levels tended to invest more in CSA technologies. Similarly, family size ($B = 0.303$, $t = 3.236$, $p \leq 0.01$) showed a positive association with adoption, implying that larger households had greater labour availability and capacity to implement multiple CSA practices. Other variables significant at the 5% level included education ($B = 0.387$, $t = 1.355$, $p \leq 0.05$) and extension contact ($B = 0.072$, $t = 1.509$, $p \leq 0.05$), suggesting

Table 3. Multiple regression analysis of selected independent variables with the level of adoption

Variable	Unstandardized Coefficient (B)	Standard Error (S.E.)	t-value
Age	-0.089	0.044	-2.033**
Marital	0.331	1.031	0.321
Family type	-0.277	0.671	-0.413
Family size	0.303	0.094	3.236**
Education	0.387	0.286	1.355*
Landholding	0.019	0.2	0.095
Income	0.101	0.10	4.051**
Extension contact	0.072	0.048	1.509*
Scientific Orientation	0.149	0.159	0.935
Attitude	-0.045	0.062	-0.721
Knowledge	0.503	0.052	9.623**

Significant pd" 0.01 level of probability $R^2 = 0.500$, F value= 13.451; *Significant pd" 0.05 level of probability

that farmers with more formal education and frequent interactions with extension personnel were more inclined to adopt CSA interventions. In contrast, age ($B = -0.089$, $t = -2.033$, $p \leq 0.01$) showed a significant negative relationship, indicating that younger farmers were more receptive to innovative agricultural practices than older ones. Marital status, family type, landholding, scientific orientation, and attitude did not demonstrate statistically significant effects in the model, indicating limited predictive power in this context. These findings highlighted knowledge, income, family size, education, and extension contact as critical determinants of CSA adoption, emphasizing the need for integrated extension programs that combine technical training with economic support mechanisms.

DISCUSSION

The present study revealed that the adoption of Climate Smart Agriculture (CSA) practices among farmers in flood-prone areas of Darbhanga was largely partial and practice-specific. Among the five CSA components assessed, crop production practices registered the highest adoption rate (49.51%), driven mainly by the use of flood-tolerant varieties and intercropping systems. This finding aligns with Kapoor & Pal (2024), who reported that low-cost, resource-efficient practices tend to gain wider acceptance among farmers compared to more capital-intensive technologies such as drip irrigation or fertigation. The prominence of legume rotations within soil fertility management further reflects farmers' recognition of natural nitrogen fixation benefits and soil health improvement.

Correlation analysis identified knowledge and income as the most significant factors positively associated with CSA adoption, supporting Singh (2020); Thakur et al., (2024) concluded that awareness and economic capacity critically influence technology uptake. Education and family size also demonstrated positive correlations, suggesting that better-educated farmers with larger household labour pools are more likely to implement diverse CSA practices. Extension contact showed a positive but statistically insignificant bivariate association; nonetheless, its role in enhancing adoption was corroborated by prior studies (Lakshmi et al., 2023; Kumar et al., 2025; Sonu & Jha, 2025), which emphasise that frequent interactions with extension personnel foster farmer confidence and awareness.

Knowledge emerged as the strongest predictor in the regression analysis, underscoring the pivotal role of information dissemination in facilitating CSA adoption. Consistent with recent literature (Erekalo & Yadda, 2023; Kirungi et al., 2023; Petros et al., 2024), the study found that access to climate-related information and education significantly shapes farmers' decisions to adopt climate-resilient practices. The absence of a clear directional effect of age on adoption, as also noted by Petros et al., (2024), suggests that factors influencing adoption are multifaceted, transcending simple demographic characteristics.

Furthermore, the study highlighted that socio-economic factors and institutional support mechanisms often outweigh physical resource endowments like landholding size in influencing CSA adoption. This observation aligns with Khoza et al., (2020); Jatav et al., (2023); Shitu & Nain (2024) who stress the importance of gender-sensitive and socio-psychological considerations in designing CSA interventions. Such nuanced understanding is crucial for developing policies that address the heterogeneity of farmer needs

and capacities. These findings collectively emphasize the urgent need for targeted, knowledge-driven extension strategies that combine technical training with economic support to enhance CSA adoption in flood-vulnerable regions like Darbhanga. Extension programs should prioritize high-impact, low-cost CSA practices, supported by demonstration plots and farmer field schools to effectively bridge the adoption gap. Additionally, institutional mechanisms offering input subsidies and facilitating peer-to-peer learning can reinforce farmers' adaptive capacities, ultimately contributing to long-term agricultural resilience.

CONCLUSION

The adoption of CSA was found to be strongly predicted by knowledge and income, suggesting that farmers who are more financially secure and knowledgeable are more likely to adopt climate-resilient practices. Crop production techniques were more widely adopted than smart water and energy interventions, indicating an uneven adoption pattern. To encourage farmers to increase adoption rates, these findings highlight the significance of expanding farmers' access to CSA knowledge through targeted extension services, field demonstrations, and training initiatives. Additionally, strengthening institutional support, providing input subsidies, and promoting farmer-to-farmer knowledge sharing are crucial strategies to expand CSA adoption. Policy measures tailored to economically vulnerable and climate-sensitive regions like North Bihar will play a vital role in fostering sustainable agricultural resilience and ensuring long-term livelihood security.

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