



Assessment of Climate Change Vulnerability among Smallholder Farmers in Cooch Behar, West Bengal

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HIGHLIGHTS

- Educational status and family size were the strongest predictors of climate vulnerability and adaptive response whereas educational status had the strongest negative correlation with both vulnerability and adaptive response indices.
- Income, land holding and expenditure lost statistical significance in regression despite strong correlation with vulnerability.

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ABSTRACT

Climate change disproportionately affects smallholder farmers, yet assessments of climate vulnerability remain limited for under-studied regions such as Cooch Behar in West Bengal. This study assessed climate-change vulnerability and adaptive response among 120 smallholder households selected through multistage sampling during 2025 in two blocks of Cooch Behar. Composite Vulnerability and Adaptive Response Indices were constructed by normalising indicators within the exposure sensitivity adaptive capacity framework (higher scores indicate greater vulnerability and greater adaptive response, respectively). The 19 independent variables were correlated with each of the two indices, and multiple regression was used to determine the significant ones. The strongest relationship with both indices was with land holding, income, expenditure and educational status, the latter correlations being non significant with family size and extension contact. Vulnerability was significantly predicted by educational status alone ($R^2 = 0.520$) while educational status, land holding and family size predicted adaptive response ($R^2 = 0.788$). The findings highlight education as a practical policy consideration for building climate-resilient smallholder households and demonstrate the utility of composite indices for identifying vulnerable households.

INTRODUCTION

Climate change is one of the most acute problems facing global agriculture, with smallholder farming systems in developing countries being most vulnerable to its negative effects (Shitu et al., 2018; Kumar et al., 2023). The changing precipitation patterns, higher temperatures, more extreme weather events and erratic monsoon behaviour in South Asia have already adversely affected agriculture, which remains the livelihood for majority of the rural

population (Yadav, 2022). India, being a predominantly agricultural country is especially susceptible to these shifts, with almost 50% of the population still engaged in agriculture, most of which is rain-fed and small-scale (Mishra et al., 2025). Cooch Behar is located in the sub-Himalayan foothill area of North Bengal and possesses unique agro-climatic conditions arising from its proximity to the Himalayas, high annual rainfall, a network of rivers and predominantly alluvial soils (Basak, 2026). Farmers in this district

are predominantly smallholders with dispersed land holdings that are highly vulnerable to climatic changes (Mishra et al., 2026). Increasing variability in rainfall distribution has changed traditional crop sequences, while flood events, riverbank erosion and occasional dry spells during critical crop-growth phases have jeopardised livelihood security (Ashoka et al., 2022; Neha et al., 2024). The study will help fill this gap in the literature on climate vulnerability in West Bengal, as Cooch Behar is a relatively under-studied area compared to other parts of the state, although it is an important agricultural region (Sodhi et al., 2023). The concept of vulnerability to climate change is a multidimensional phenomenon and is generally defined as the result of exposure, sensitivity and adaptive capacity (Serkendiz & Tatli, 2023). According to Zhai and Lee (2024), exposure is the level of climatic stress that a system must endure, sensitivity is the degree to which the system is susceptible to climatic stress, and adaptive capacity is the ability of a system to modify and cope in response to climatic stress. Combined assessment of these dimensions is more comprehensive than the evaluation of climatic exposure alone, because it includes the socio-economic, institutional and infrastructural aspects that affect farmers' vulnerability to shocks and impacts due to climate change, and their capacity to recover (Singh et al., 2025). Farmers may efficiently adapt to and reduce the consequences of climate change by putting precise conservation agriculture strategies into practice (Shitu & Nain, 2024). In this context a spatial vulnerability assessment is especially useful because vulnerability is rarely even over a geographical area. However, within relatively small administrative units, vulnerability can vary due to soil-type, availability of irrigation water, intensity of use, road accessibility and socio-economic status (Kumar et al., 2026). The use of composite index techniques in concert with field-based socio-economic data can help researchers determine vulnerable areas and help inform more targeted and efficient policy action.

METHODOLOGY

The study was conducted in Cooch Behar district of West Bengal, which lies in the sub-Himalayan foothill agro-climatic zone of North Bengal and is climatically sensitive owing to high rainfall, a dense river network and predominantly alluvial soils (Basak, 2026). An ex-post-facto research design was adopted and a multistage sampling procedure was used to the selected sample. Cooch Behar-II and Dinhata-II blocks were purposively selected on the basis of agro-climatic diversity and exposure to floods, riverbank erosion and rainfall variability; villages and farming households were then randomly selected within those blocks, Khagribari and Singimari Paschimpar villages were selected randomly, while Durganagar and Hokadaha-I were selected from each blocks randomly. From each villages, thirty respondents were randomly selected. The final sample comprised 120 farming households.

Primary data were collected through a pre-tested interview schedule administered to the sampled farmers. Secondary data on rainfall, land use and demographics were obtained from district records and supplemented by literature and expert consultation during 2025. The Vulnerability Index and the Adaptive Response Index were constructed independently of the nineteen predictor variables later used in the correlation and regression analyses.

Following the exposure–sensitivity–adaptive capacity framework (Serkendiz & Tatli, 2023; Zhai & Lee, 2024), indicators of exposure (e.g., rainfall variability), sensitivity (e.g., frequency of flood and dry-spell events) and adaptive capacity (e.g., irrigation access, adoption of climate-resilient practices, coping mechanisms) were elicited for every household. To ensure that the various variables measured on different scales contributed similarly to the total scores, the various component indicators were subjected to a min-max normalisation process by (Iyengar & Sudarshan, 1982), and then the normalised sub-indicators were added together to create the composite scores at the household level, the Vulnerability Index and the Adaptive Response Index. None of these nineteen independent variables described were included in the construction of these indices, but were used, as reported in the Results, to examine correlations with and statistically explain the variance in the two indices.

Data were coded and analysed with conventional statistical software SPSS version 27. The bivariate relationship between the nineteen independent variables and the Vulnerability and Adaptive Response indices was determined using Pearson's product moment correlation coefficient were computed between each of the nineteen independent variables and the two indices.. The significant determinants of each index were then identified using multiple linear regression analysis and then performed. The general form of the models was:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_{19} X_{19} + \epsilon$$

Where, Y denotes the Vulnerability Index or the Adaptive Response Index. Unstandardised coefficients (B), standard errors, standardised beta coefficients (β) and t-values were obtained. Statistical significance was assessed at the 5 per cent level.

RESULTS

Correlation between independent variables and the vulnerability and adaptive response indices

Table 1 presents the Pearson correlation coefficients between the nineteen independent variables and the two outcome indices. Age (X1) and years of farming experience (X4) were positively and significantly associated with both indices. Educational status (X2) exhibited the strongest negative correlations with vulnerability ($r = -0.487$) and adaptive response ($r = -0.598$) for all the socio-personal variables. Land holding (X5), annual household income (X6), annual expenditure (X7) and material possession (X8) likewise showed highly significant negative correlations. Information-seeking behaviour (X11), management orientation (X17) and awareness of climate change (X19) were also negatively related to both indices. Family size (X3), extension contact (X9), access of information sources (X10), innovative proneness (X12), change resistance (X13), risk-bearing ability (X14), scientific orientation (X15) and economic motivation (X16) did not display statistically significant bivariate associations.

Predictors of the vulnerability index: Multiple regression

The multiple regression model for the Vulnerability Index explained 52.0 per cent of the total variance (Table 2). Two

Table 1. Correlation between independent variables and vulnerability and adaptive response indices

Independent variable	Vulnerability Index (X20)	Adaptive Response Index (X21)
Age (X1)	0.190*	0.260**
Educational status (X2)	-0.487**	-0.598**
Family size (X3)	0.035	-0.020
Years of experience in farming (X4)	0.207*	0.288**
Land holding (X5)	-0.547**	-0.733**
Annual household income (X6)	-0.531**	-0.727**
Annual expenditure (X7)	-0.517**	-0.717**
Material possession (X8)	-0.291**	-0.420**
Extension contact (X9)	0.030	-0.013
Access of information sources (X10)	-0.142	-0.143
Information seeking behaviour (X11)	-0.210*	-0.245**
Innovative proneness (X12)	0.088	0.091
Change resistance (X13)	-0.037	-0.024
Risk bearing ability (X14)	-0.117	-0.103
Scientific orientation (X15)	-0.155	-0.147
Economic motivation (X16)	-0.125	-0.102
Management orientation (X17)	-0.187*	-0.227*
Experienced change (X18)	-0.128	-0.167
Awareness regarding climate change (X19)	-0.234*	-0.266**

Note: * $p < 0.05$; ** $p < 0.01$. $n = 120$.

predictors were statistically significant at the 5 per cent level: educational status (X2; $\beta = -0.373$, $t = -4.680$) exerted a negative influence, while family size (X3; $\beta = 0.171$, $t = 2.090$) exerted a positive influence. No other variables reached statistical significance ($|t| < 1.96$). Although annual household income, land holding and annual expenditure displayed relatively large coefficient magnitudes, they were not statistically significant.

The multiple regression model for the Vulnerability explained 52.0 per cent of the total variance (Table 2). Two predictors of the

Vulnerability Index were statistically significant; educational status (X2) had a negative significant ($\beta = -0.373$, $t = -4.680$) and the family size (X3) had a positive significant ($\beta = 0.171$, $t = 2.090$) showed a significant influence (Figure 1). There were no other variables that were significant ($|t| < 1.96$). Annual household income (X6, $\beta = -0.905$), land holding (X5, $\beta = -0.276$) and annual expenditure (X7, $\beta = 0.728$) had the highest coefficient magnitudes in absence of significance. Other factors such as age, awareness, access to information, scientific orientation and behaviour characteristics like economic motivation, risk-bearing capacity, and innovative proneness exhibited slight and insignificant effects.

Predictors of the adaptive response index: Multiple regression

The multiple regression model, which was used to identify the determinants of the Vulnerability accounted for 78.8 per cent of the total variance as shown in Table 3. There were three predictors that were statistically significant for the Adaptive Response Index (Figure 2). Educational status (X2) showed the strongest negative influence ($\beta = -0.462$, $t = -8.652$), followed by land holding (X5, $\beta = -0.304$, $t = -2.265$). The number of family members (X3) had a significant positive effect ($\beta = 0.167$, $t = 3.051$). All other 16 variables were non-significant with $|t| < 1.96$. The largest coefficients were for annual household income (X6, $\beta = -0.825$), annual expenditure (X7, $\beta = 0.443$), but these two factors were not significant. Other variables such as age, awareness, innovative proneness and information seeking behaviour were found to have small without any significant effect.

DISCUSSION

Economic resource variables land holding, income and expenditure; displayed the strongest bivariate associations with both vulnerability and adaptive response, consistent with Ghosh and Ghosal (2020) in the neighbouring sub-Himalayan foothills of West Bengal. The strongest non-material correlate was educational status,

Table 2. Multiple regression analysis of factors influencing the Vulnerability Index

Independent variable	B	SE	β	t	p-value
Age (X1)	-0.0009	0.0008	-0.221	-1.164	0.247
Educational status (X2)	-0.0037	0.0008	-0.373	-4.680**	<0.001
Family size (X3)	0.0052	0.0025	0.171	2.090*	0.039
Years of experience in farming (X4)	0.0006	0.0007	0.141	0.756	0.451
Land holding (X5)	-0.0100	0.0073	-0.276	-1.380	0.171
Annual household income (X6)	-0.0020	0.0017	-0.905	-1.172	0.244
Annual expenditure (X7)	0.0019	0.0018	0.728	1.011	0.314
Material possession (X8)	0.0003	0.0012	0.026	0.280	0.780
Extension contact (X9)	0.0049	0.0027	0.213	1.802	0.075
Access of information sources (X10)	-0.0040	0.0025	-0.195	-1.646	0.103
Information seeking behaviour (X11)	-0.0003	0.0010	-0.029	-0.347	0.729
Innovative proneness (X12)	0.0018	0.0042	0.061	0.436	0.664
Change resistance (X13)	-0.0038	0.0045	-0.113	-0.840	0.403
Risk bearing ability (X14)	-0.0004	0.0017	-0.029	-0.246	0.806
Scientific orientation (X15)	-0.0017	0.0013	-0.120	-1.351	0.180
Economic motivation (X16)	-0.0009	0.0036	-0.028	-0.236	0.814
Management orientation (X17)	0.0004	0.0010	0.035	0.373	0.710
Experienced change (X18)	0.0003	0.0004	0.105	0.862	0.391
Awareness regarding climate change (X19)	-0.0016	0.0011	-0.179	-1.467	0.145

Model summary: $R = 0.721$; $R^2 = 0.520$; Adjusted $R^2 = 0.428$; $SE = 0.0268$; $n = 120$.

Figure 1. Multiple regression analysis of factors influencing vulnerability index

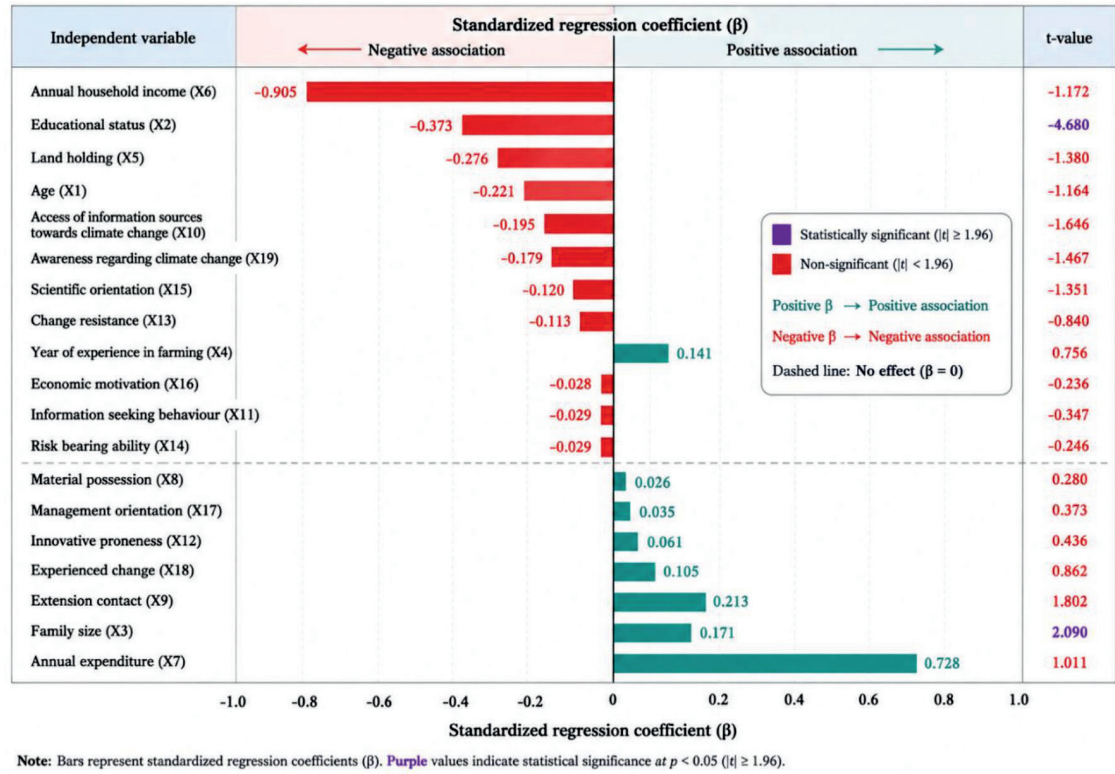


Table 3. Multiple regression analysis of factors influencing the Adaptive Response Index

Independent variable	B	SE	β	t	p-value
Age (X1)	-0.0019	0.0014	-0.171	-1.349	0.180
Educational status (X2)	-0.0124	0.0014	-0.462	-8.652**	<0.001
Family size (X3)	0.0139	0.0046	0.167	3.051**	0.003
Years of experience in farming (X4)	0.0010	0.0013	0.089	0.712	0.478
Land holding (X5)	-0.0299	0.0132	-0.304	-2.265*	0.026
Annual household income (X6)	-0.0049	0.0031	-0.825	-1.597	0.113
Annual expenditure (X7)	0.0031	0.0034	0.443	0.919	0.360
Material possession (X8)	0.0003	0.0022	0.009	0.146	0.884
Extension contact (X9)	0.0016	0.0050	0.025	0.320	0.749
Access of information sources (X10)	-0.0022	0.0045	-0.039	-0.486	0.628
Information seeking behaviour (X11)	-0.0012	0.0018	-0.037	-0.660	0.511
Innovative proneness (X12)	-0.0074	0.0076	-0.092	-0.972	0.333
Change resistance (X13)	0.0003	0.0082	0.003	0.036	0.971
Risk bearing ability (X14)	0.0008	0.0030	0.021	0.267	0.790
Scientific orientation (X15)	-0.0011	0.0024	-0.028	-0.473	0.638
Economic motivation (X16)	-0.0003	0.0066	-0.004	-0.048	0.962
Management orientation (X17)	0.0002	0.0018	0.008	0.123	0.903
Experienced change (X18)	0.0003	0.0007	0.038	0.462	0.645
Awareness regarding climate change (X19)	-0.0028	0.0020	-0.112	-1.368	0.174

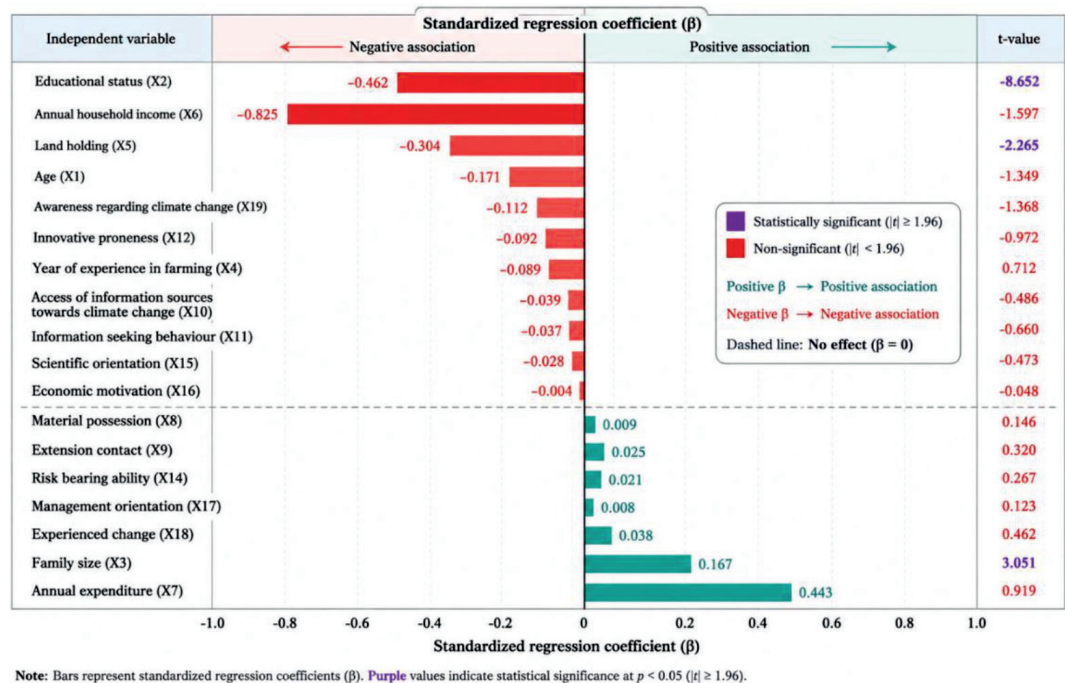
Model summary: $R=0.886$; $R^2=0.788$; Adjusted $R^2=0.744$; Standard error of estimate=0.0487. $n=120$.

which correlated with Jatav (2024) who found illiterate farmers in Uttar Pradesh to be more vulnerable than their literate counterparts. The slight positive association between age and farming experience and vulnerability is in contrast to Sarkar et al. (2026) who found younger farmers adopting more easily, which may be interpreted as the older farmers continuing to follow traditional farming methods but not as a reversal of risk. The modest associations in awareness were similar to Patel et al. (2023) who noted that monetary

motivation was a more significant driver of adaptation among Indian farmers than climate knowledge.

In the multivariate models, educational status and family size significantly predicted the Vulnerability Index, while educational status, land holding and family size significantly predicted the Adaptive Response Index. These results are consistent with Jatav (2024) in underscoring the sustained negative association of education with vulnerability. The positive coefficient of family size

Figure 2. Multiple regression analysis of factors influencing adaptive response index



suggests that a larger dependency burden may constrain adaptive investments, although larger households can also supply labour (Sarkar et al., 2026). Although land holding, income and expenditure were strongly correlated with both indices, they lost independent statistical significance once entered jointly.

Behavioural and psychological variables were generally weak and non-significant, suggesting that their influence, if any, is largely indirect. Methodologically, the composite-index approach employed here is consistent with previous applications of composite vulnerability indices to Indian farm households (e.g., Balaganesh & Sendhil, 2025). Overall, economic and educational determinants of vulnerability appear broadly similar across agro-climatic regions of India, whereas age and household-structure effects appear more context-specific.

CONCLUSION

The study examined the climate-change vulnerability of smallholder farmers in Cooch Behar, West Bengal, using composite Vulnerability and Adaptive Response Indices constructed from household-level exposure, sensitivity and adaptive-capacity indicators. Most sampled households fell into the medium vulnerability category, and educational status, family size, and land holding emerged as the most consistent statistical determinants of both indices, while income and expenditure, though strongly correlated, lost independent significance due to multicollinearity. These findings, consistent with recent evidence from other Indian agro-climatic regions, position education as a central policy lever for vulnerability reduction and highlight household structure and asset base as important, non-behavioural drivers requiring targeted intervention. The study reinforces the value of composite indices for identifying vulnerable households and offers an evidence base for designing region-specific adaptation strategies.

DECLARATIONS

Ethical consideration and consent to participate: All procedures performed in studies involving human participants were in accordance with the ethical standards of social research. The Divisional review board, Agricultural Extension Division, of UBKV, Cooch Behar waived the ethical approval vide reference no. UBKV/ Agril. Extn./204/206 dated 18.08.2026. All respondents participated voluntarily after receiving an explanation of the research objectives, the benefits of the research, and assurances of data confidentiality. The verbal consent of respondents was obtained and their identity is kept confidential and is used only for academic purposes.

Conflict of interest: The authors have declared that no conflict of interest, financial or non-financial, exists that could affect the implementation, analysis, or reporting of the results of this research.

Consent for publication: The authors give their consent for publication of the manuscript in the journal, if accepted.

Data Availability statement: The data generated and analyzed in this project are not publicly available due to participant level information, ethical and confidentiality issues. The associated author will provide the dataset, upon reasonable request, subject to relevant institutional and ethical constraints.

Authors' contribution: Anubhab Karjee conducted the field investigation, data collection, statistical analysis. Kausik Pradhan supervised the study and contributed to research design and interpretation of results. Swapnamay Ghosh, Praveenkumar Marimuthu, Chigilipalli Mounika and Atreyee Sarkar assisted in literature review, data interpretation, manuscript preparation and editing. All authors read and approved of the final manuscript.

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REFERENCES

- Ashoka, N., Harshavardhan, M., Hongal, S., Meti, S., Raju, R., Patil, G. I., & Shashidhara, N. (2022). Farmers' acuity on climate change in the central dry zone of Karnataka. *Indian Journal of Extension Education*, 58(3), 136–141. <https://doi.org/10.48165/IJEE.2022.58328>
- Balaganesh, G., & Sendhil, R. (2025). Development of household vulnerability index to climate change induced drought: Empirical evidence from rural farm households in Tamil Nadu, India. *Environment, Development and Sustainability*. <https://doi.org/10.1007/s10668-025-06095-6>
- Basak, R. (2026). Rainfall variability and agricultural productivity: A case study in Cooch Behar district of West Bengal, India. *Saudi Journal of Humanities and Social Sciences*, 11(3), 84–90. <https://doi.org/10.36348/sjhss.2026.v11i03.002>
- Ghosh, M., & Ghosal, S. (2020). Determinants of household livelihood vulnerabilities to climate change in the Himalayan foothills of West Bengal, India. *International Journal of Disaster Risk Reduction*, 50, 101706.
- Iyengar, N. S., & Sudarshan, P. (1982). A method of classifying regions from multivariate data. *Economic and Political Weekly*, 17(51), 2047–2052.
- Jatav, S. S. (2024). Farmers' perception of climate change and livelihood vulnerability: A comparative study of Bundelkhand and Central regions of Uttar Pradesh, India. *Discover Sustainability*, 5, 11. <https://doi.org/10.1007/s43621-024-00193-7>
- Kumar, A., & Mohanasundari, T. (2025). Assessment of livelihood vulnerability to climate change among tribal communities in Chhindwara and Dhar district, Central India. *Scientific Reports*, 15, 8843. <https://doi.org/10.1038/s41598-025-90769-8>
- Kumar, A., Mishra, V. K., Mandal, U., Kaushal, R., Roy, T., Garg, S., & Madhu, M. (2026). Flood risk zonation and agricultural vulnerability assessment using AHP and land use analysis in the Burhi Gandak basin in Lower Gangetic Plains, India. *Natural Hazards*, 122(11), 471.
- Kumar, K. N. R., Reddy, M. J. M., Reddy, K. V., Paramesha, V., Balasubramanian, M., Kumar, T. K., Kumar, R. M., & Reddy, D. D. (2023). Determinants of climate change adaptation strategies in South India: Empirical evidence. *Frontiers in Sustainable Food Systems*, 7, 1010527. <https://doi.org/10.3389/fsufs.2023.1010527>
- Mishra, G., Gupta, B. K., Mishra, B. P., Verma, A. P., Mishra, D., & Shukla, G. (2026). Assessing climate change adaptation strategies among livestock rearers in Bundelkhand region, India. *Indian Journal of Extension Education*, 62(1), 129–134. <https://doi.org/10.48165/IJEE.2026.62121>
- Sodhi, G. P. S., Singh, R. K., Dhillon, G. S., Ahuja, S., Kaur, A., Sunidhi, Kaur, T., Murai, A. S., Singh, R., & Kaur, S. (2023). Adoption behaviour of climate-resilient agricultural practices in Punjab under NICRA project. *Indian Journal of Extension Education*, 59(2), 46–50. <https://doi.org/10.48165/IJEE.2023.59210>
- Nallamuthu, P., Sriram, N., Karthikeyan, C., Lourdasamy, D. K., & Prahadeeswaran, M. (2026). Climate resilience in coconut farming systems: A systematic review and bibliometric analysis of vulnerability and adaptation. *Genetics and Molecular Research*, 25(12s). <https://doi.org/10.4238/pncqwa70>
- Neha, Rawat, M., & Upasana. (2024). Exploring proximate determinants of farmers adaptation measures to climate change: A comprehensive review. *International Journal of Agriculture Extension and Social Development*, 7(7S), 101–107. <https://doi.org/10.33545/26180723.2024.v7.i7Sb.781>
- Patel, S., Mall, R. K., Chaturvedi, A., Singh, R., & Chand, R. (2023). Passive adaptation to climate change among Indian farmers. *Ecological Indicators*, 154, 110637. <https://doi.org/10.1016/j.ecolind.2023.110637>
- Sarkar, S., Mukherjee, A., Biswas, A., Gorain, S., Bera, B., Giri, A., Roy Choudhury, M., Dutta, S., & Das, S. (2026). Evaluating farmers' strategies and socioeconomic drivers for adaptation to climate uncertainty: A case study in the Himalayan region of West Bengal, India. *Regional Sustainability*, 7(2), 100334. <https://doi.org/10.1016/j.regsus.2026.100334>
- Serkendiz, H., & Tatli, H. (2023). Assessment of multidimensional drought vulnerability using exposure, sensitivity, and adaptive capacity components. *Environmental Monitoring and Assessment*, 195(10), 1154. <https://doi.org/10.1007/s10661-023-11711-x>
- Shitu, A. G., Nain, M. S., & Singh, R. (2018). Developing extension model for smallholder farmers uptake of precision conservation agricultural practices in developing nations: Learning from rice-wheat system of Africa and India. *Current Science*, 114(4), 814–825.
- Shitu, A. G., & Nain, M. S. (2024). Benefits of precision conservation agriculture practices as perceived by Indo-Gangetic Plain (IGP) community for climate-smart agriculture, *SKUAST Journal of Research*, 26(2), 219–226. <https://doi.org/10.5958/2349-297X.2024.00029.2>
- Singh, S., Das, J., Goyal, A. K., & Mohanty, S. K. (2025). Spatial pattern of climatic exposure and multidimensional poverty in districts of India. *Sustainable Cities and Society*, 130, 106530. <https://doi.org/10.1016/j.scs.2025.106530>
- Yadav, M. (2022). South Asian monsoon extremes and climate change. In *Extremes in atmospheric processes and phenomenon: Assessment, impacts and mitigation* (pp. 59–86). Springer Nature Singapore.
- Zhai, L., & Lee, J. E. (2024). Investigating vulnerability, adaptation, and resilience: A comprehensive review within the context of climate change. *Atmosphere*, 15(4), 474. <https://doi.org/10.3390/atmos15040474>