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RESEARCH

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A field-based data-driven modeling approach for livelihood vulnerability examination of rice farmers' considering climate risk in parts of West Bengal, Eastern India

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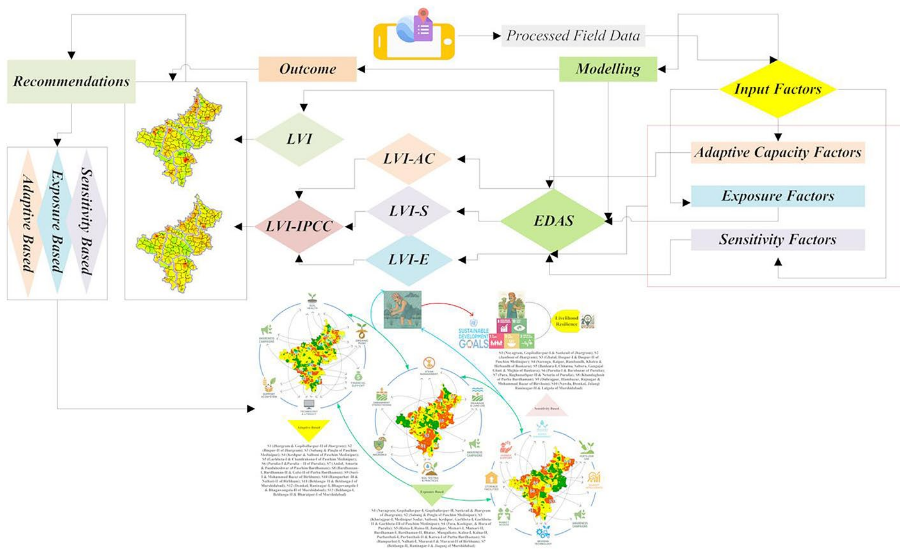
Abstract

Agriculture is crucial for the rural economy in India, making it essential to assess how environmental and climatic changes impact rice farmers' livelihoods. This study employed the Evaluation based on Distance from Average Solution (EDAS) model for a multi-criteria decision analysis method, to compute a Livelihood Vulnerability Index (LVI) and an IPCC-based LVI, reflecting rice farmers' adaptive capacity, exposure, and sensitivity. Data from 1814 rice farmers across eight districts in West Bengal were collected in 2023. In 2023, field surveys of 1814 rice farmers across eight West Bengal districts were conducted. The LVI values ranged from 0.17 to 0.93, with an ROC-AUC accuracy of a model classification accuracy (ROC-AUC) of 0.89. LVI-AC ranged from 0.02 to 0.97, LVI-E and LVI-S from 0.00 to 1.00, and LVI-IPCC values from −0.48 to 0.54, with an ROC-AUC accuracy of 0.86. Component indices varied widely: adaptive capacity (LVI-AC) ranged from 0.02 to 0.97, and exposure/sensitivity (LVI-E/S) from 0.00 to 1.00. The composite LVI-IPCC ranged from −0.48 to 0.54 (ROC-AUC = 0.86). District-level analysis showed that Birbhum and Murshidabad were the most vulnerable districts, whereas Purba and Paschim Bardhaman were relatively less vulnerable (e.g. nearly half of Murshidabad's area was highly vulnerable vs. less than 10% in Purba Bardhaman). Adaptive capacity was lowest in Jhargram and Paschim Bardhaman, reflecting limited adaptation resources, whereas Purba Bardhaman was the most exposed to climate risk. In contrast, exposure vulnerability was minimal in Bankura. Sensitivity to climate hazards was highest in Bankura and Jhargram. The LVI-IPCC analysis identified Birbhum as highly vulnerable to climate change. Notably, the combined LVI-IPCC measure singled out Birbhum as particularly vulnerable to climate change impacts. By highlighting livelihood vulnerabilities, this study informs interventions that support poverty reduction and food security (SDGs 1–3) while promoting sustainable economic growth (SDG 8) and climate resilience (SDG 13). The approach provides a practical tool for policymakers to target adaptation strategies and enhance climate-adaptive farming practices among vulnerable communities.

Keywords Rural livelihood, Livelihood vulnerability index (LVI), Livelihood resilience, Adaptive capacity, Exposure, Sensitivity, LVI-IPCC framework, Data-driven modeling, Site-specific recommendations, Food security, Sustainable Development Goals (SDGs)

Graphical Abstract



1 Introduction

Agriculture, as the backbone of rural economies in India, is increasingly threatened by climate change, natural resource degradation, and socio-economic disparities [1]. These interconnected stressors have a particularly profound effect on rice farmers, whose livelihoods rely on weather-sensitive cropping systems and limited institutional support. To address these challenges, the Livelihood Vulnerability Index (LVI) and its IPCC-adapted version (LVI-IPCC) have been widely used to assess livelihood risks by integrating three core components-adaptive capacity, exposure, and sensitivity [2, 3]. These tools help policymakers, researchers, and development practitioners identify vulnerable groups, design targeted adaptation measures, and monitor progress toward global sustainability goals. They also contribute directly to the United Nations Sustainable Development Goals (SDGs 1, 2, 8, and 13) by supporting evidence-based strategies for resilience building and food security. LVI examines a variety of factors that can affect farmers, like the amount of rain they receive, 41 their income, their education, and so on. It enables governments and groups to determine where 42 farmers are most vulnerable and how to assist them. The LVI-IPCC emphasizes how climate 43 change impacts farmers. It helps us to assess whether farmers are struggling due to factors such as 44 changing weather patterns. These technologies are also vital in achieving the United Nations 45 Sustainable Development Goals (SDGs) for a better future [4–6].

West Bengal, an eastern Indian state, presents a mosaic of agro-climatic zones that reflect broader regional vulnerability patterns. The study focuses on eight agriculturally significant districts: Jhargram, Paschim Medinipur, Bankura, Purulia, Purba Bardhaman, Paschim Bardhaman, Birbhum, and Murshidabad. These districts span lateritic uplands and alluvial floodplains, characterized by diverse challenges such as erratic monsoon rainfall, groundwater depletion, pest outbreaks, and soil degradation. Given this diversity, West Bengal offers a representative case to evaluate livelihood vulnerability in Eastern India, making it suitable for detailed investigation under LVI-IPCC frameworks. Several global and national studies have demonstrated the utility of composite indices like LVI and LCI in assessing livelihood vulnerability. In China, studies conducted in Tibet and Zunyi City applied LCI-based methods to assess household adaptation and sustainability [7–10]. In the Vietnam Mekong Delta (VMD), triple-cropping systems, dike construction, and extreme weather have been shown to compromise farming livelihoods, increase mechanization, and reduce labor demand [11–18]. In the Indian context, particularly West Bengal, recent studies indicate increasing vulnerability of rice farmers to both climatic and socio-economic stressors [19]. Spatial analyses show that 92.14% of cultivable land in Bankura requires adaptive interventions [20], while in Islampur, only 10.84% of land exhibits high aquifer recharge potential [21]. In addition, disparities in access to livelihood capitals contribute to entrenched rural poverty [22].

Despite these studies, there is a clear gap in research that combines primary field-based household data with multi-criteria decision-making models under the LVI-IPCC framework. Existing studies often rely on secondary datasets or apply LVI frameworks without integrating decision-support models. To our knowledge, the Evaluation based on Distance from Average Solution (EDAS) model-a robust and objective ranking method-has not yet been used for LVI-IPCC analysis in the Indian agricultural context. This creates a gap in localized vulnerability assessments and limits policy guidance at the micro-regional level.

This study aims to evaluate the livelihood vulnerability of rice farmers across eight districts in West Bengal using an EDAS-integrated LVI and LVI-IPCC model. Specifically, it seeks to assess the relative contributions of adaptive capacity, exposure, and sensitivity to overall vulnerability and identify spatial patterns that inform targeted interventions.

The research is guided by the following key questions:

- What is the level of livelihood vulnerability among rice farmers in the eight districts of West Bengal under conditions of climate uncertainty?
- How do the components of adaptive capacity, exposure, and sensitivity contribute to the overall LVI and LVI-IPCC values?
- Which districts exhibit the highest levels of vulnerability, and what are the underlying factors?
- Which of the three components (adaptive capacity, exposure, or sensitivity) most significantly influences vulnerability across districts?
- How can the LVI and LVI-IPCC results guide effective policy-making and resilience strategies for rice farming communities in West Bengal?

To address these questions, the study utilized primary data collected from 1814 rice-farming households across eight districts of West Bengal during 2023. A total of 17 indicators were selected and classified into the three core components of the LVI and LVI-IPCC frameworks—adaptive capacity, exposure, and sensitivity—based on both field relevance and insights from existing literature. The adaptive capacity indicators include farmer age, household size, education level, fertilizer cost (including N-P-K and additional nutrients), and revenue from pulses per hectare, reflecting generational knowledge, labor availability, financial investment, and income diversification [23–28]. The exposure indicators consist of crop vulnerability to weather and climate, soil moisture condition during harvesting, prevalence of pests, diseases and weeds, access to critical weather information, and key climatic factors such as rainfall and temperature [29–37]. Sensitivity indicators include utilization of digital tools, yield in tons per hectare, availability of quality rice fallow pulse seeds, frequency of RFP adoption after Kharif, presence of soil problems (e.g., salinity or hardpan), and frequency of land being left fallow post-Kharif [2, 38–42]. These 17 influencing parameters offer a robust, context-specific framework for capturing the multidimensional nature of livelihood vulnerability among rice farmers in climate-sensitive environments. The values were analyzed using the Evaluation based on Distance from Average Solution (EDAS) model, and the model's performance was validated through ROC-AUC analysis, enabling a spatially differentiated assessment that supports targeted adaptation strategies and resilience planning.

2 Study area

The present study covers eight agriculturally significant districts of West Bengal, India-Jhargram, Paschim Medinipur, Bankura, Purulia, Purba Bardhaman, Paschim Bardhaman, Birbhum, and Murshidabad-representing a gradient of physiographic, climatic, and socio-economic conditions. These districts span three distinct agro-ecological belts: the western lateritic plateau, the central Rarh transitional zone, and the eastern alluvial floodplain, making them ideal for assessing spatial variations in livelihood vulnerability among rice-farming communities. Jhargram, located between the Subarnarekha and Kangsabati rivers, is known for its predominantly rural and tribal (notably Santal) population. It lies between 21° 45′ N to 22° 42′ N latitude and 86° 42′ E to 87° 16′ E longitude, covering an area of 3037.64 km^2 and housing a population of 1,136,548. Agriculture is the dominant livelihood source. Paschim Medinipur spans 12,936 km^2, with a population of 5,943,300-of which 3,938,868 live in rural areas. Agriculture contributes approximately 60% of the district's GDP. Bankura has a population of 3,596,674 and an area of 6882 km^2, with agriculture contributing about 70% to the local economy. Purulia, predominantly agricultural, spans 6259 km^2 and has a population of 2,927,965. In the central transitional zone, Purba Bardhaman covers 4152 km^2 and has a population of 5,819,826, while Paschim Bardhaman, more urban-industrial in nature, spans 7024 km^2 with 2,882,031 residents. Birbhum, located between 23° 32′ 30″ N to 24° 35′ 0″ N latitude and 87°5′25″ E to 88° 1′ 40″ E longitude, spans 4545 km^2 with a population of 3,502,404, where agriculture remains the economic mainstay despite mixed land quality. Murshidabad, in the eastern alluvial plains, lies between 23° 43′ N to 24° 52′ N latitude and 87°49′ E to 88°44′ E longitude, spanning 5324 km^2 and hosting 7,103,807 people, including 5,071,599 in rural areas. Its fertile soils and ample monsoonal rainfall support intensive rice production, though flood risks and environmental concerns persist. Rice is the dominant Kharif crop across the region, but its cultivation is challenged by varying land use patterns, inconsistent crop management, and limited adoption of rice-fallow pulse (RFP) practices. These factors influence the vulnerability of farming communities in different physiographic zones.

To capture these regional disparities, the study incorporates climatic, hydrogeological, and environmental stressors based on literature and field experience. In the western lateritic plateau districts-Purulia, Bankura, Jhargram, and Paschim Medinipur-agriculture is constrained by hard-rock aquifers, with 26.1% of groundwater samples unfit for irrigation [43]. Rainfall is often erratic and below 1300 mm/year, while summer temperatures exceed 45 °C, contributing to drought-like conditions and reduced rice productivity. In the central Rarh belt-Birbhum, Purba Bardhaman, and Paschim Bardhaman-soils support both rainfed and irrigated rice, but the depletion of groundwater due to intensive extraction, coupled with temperature rise at 0.22 °C per decade, threatens sustainability [6]. Murshidabad, in the eastern alluvial zone, benefits from high rainfall (> 1500 mm/year) and rich soils, but is increasingly vulnerable to monsoon flooding and arsenic contamination in irrigation sources, with 32.2% of groundwater samples found unsuitable for use [5]. By integrating these hydro-environmental indicators with socio-ecological and demographic datasets, the study develops a spatially explicit model to assess district-level livelihood vulnerability among rice-farming households in West Bengal (Fig. 1).

3 Materials

3.1 Survey design

A purposive sampling technique was employed to collect data from 1814 rice farmers across eight districts of West Bengal. This method was chosen to ensure that a diverse range of agro-ecological and livelihood conditions-including rice-fallow-pulse (RFP) cultivation intensity, exposure to climate risks, and variability in adaptive capacity-were adequately captured. The selection of sites prioritized areas with high agricultural dependence, visible climate impacts (e.g., erratic rainfall, pest outbreaks), and known variations in rice productivity. This strategy ensured contextual richness while supporting the study's objective of identifying spatially differentiated vulnerability patterns. Prior to the main survey, a pilot phase was conducted involving farmers, agricultural input providers, local elders, and government officials. Feedback from this stage was used to refine the questionnaire for clarity and cultural appropriateness. To ensure spatial accuracy and control potential field-level data falsification, a custom geo-coding script was embedded in the Google Form used for data collection. This script automatically captured the real-time geographic coordinates (latitude/longitude) of each response upon submission. The mobile-based Google Form, along with KML support for Google Earth navigation, enabled efficient targeting of survey locations and avoided spatial overlap. Surveyors underwent intensive training on field protocols, communication techniques, and ethical conduct. Post-training assessments and continuous field supervision were conducted to maintain data quality. Additionally, geo-tagged photographs were taken to validate site conditions and cross-reference reported information. This integrated design ensured that the survey achieved both spatial representativeness and field authenticity across the study area.

3.2 Role of GIS for LVI and LVI-IPCC

GIS facilitates navigation by integrating GPS data acquired on the ground to precisely identify and attribute data points. This ensures accurate mapping and analysis. In this study, ArcGIS 10.8 software was used to manage and process all geospatial data layers. GIS uses spatial interpolation techniques to estimate values in unsampled places. We employed the Inverse Distance Weighting (IDW) interpolation method to extrapolate LVI and LVI-IPCC values from sampled GPS points to un-sampled areas, as it provides a simple yet effective distance-based weighting suitable for relatively dense field samples. For example, the LVI and LVI-IPCC values of a GPS-based sample location can be

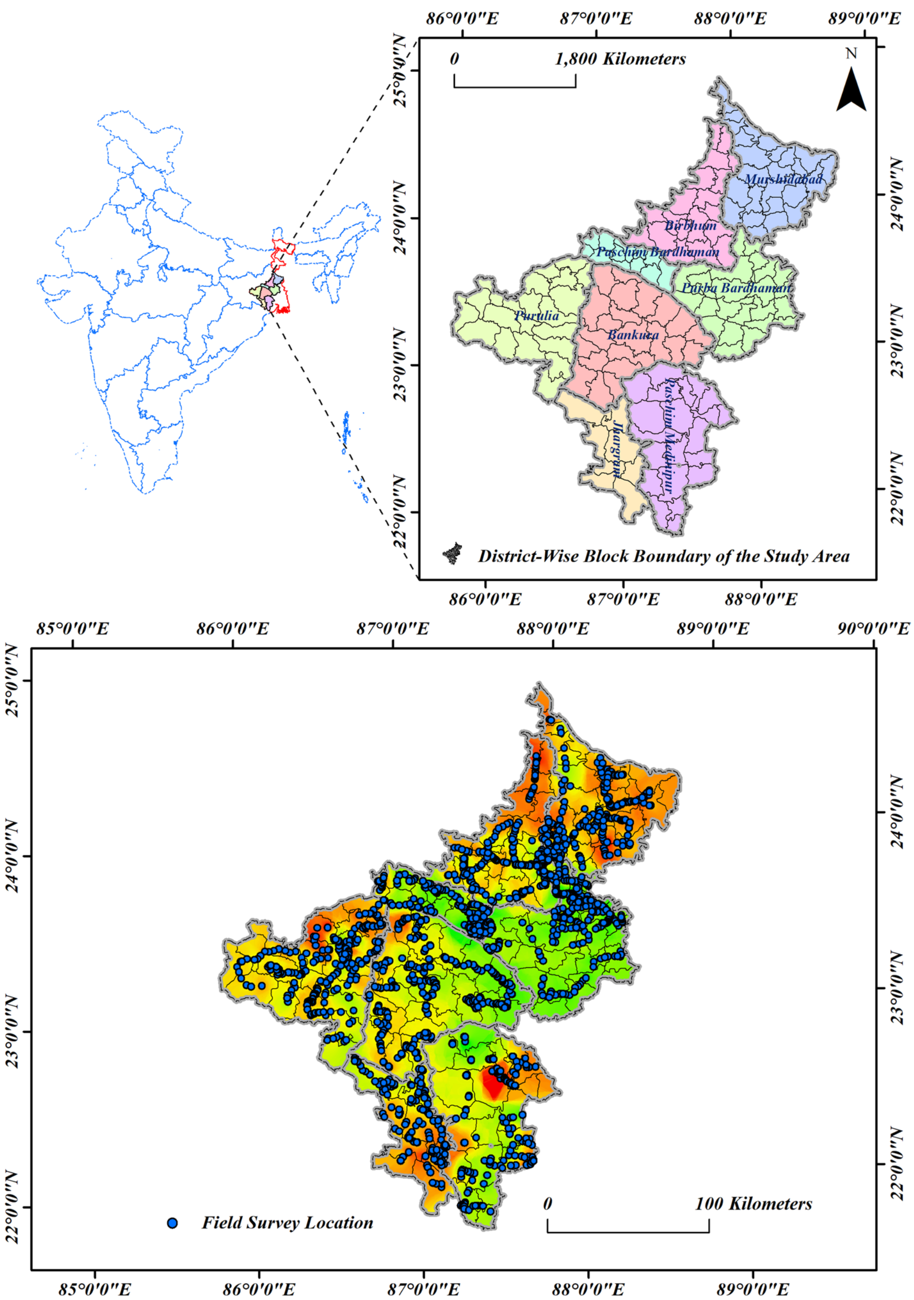


Fig. 1 Location map of the study area with field sites

used to determine the vulnerability levels of un-sampled areas. GIS is critical for LVI and LVI-IPCC study because it integrates, analyzes, and visualizes data relating to adaptive capacity, exposure, and sensitivity. This comprehensive approach helps decision-makers identify susceptible areas and apply targeted interventions to promote sustainable agricultural growth and livelihood quality measurement. To maintain standard terminology throughout, we consistently refer to adaptive capacity in alignment with the LVI-IPCC framework. GIS aids in understanding the circumstances surrounding each of the adaptive capacity, exposure, and sensitivity variables.

3.3 Field-based conditioning factors

All field-based conditioning factors were incorporated into the model. These factors were classified using a perception-based approach (in the absence of fixed thresholds), developed through focused interactions with local farmers and domain experts. The classification outcomes are presented in Tables 1, 2 and 3, and all percentage values were computed based on field data from 1814 samples across eight districts in West Bengal.

3.3.1 Adaptive capacity

Adaptive capacity refers to the socio-demographic characteristics, social networks, and livelihood strategies that enable farmers to respond to and cope with environmental and economic challenges [2]. The following field-derived indicators were used to assess adaptive capacity:

The age of farmers influences agricultural experience and adaptability, with older farmers facing moderate vulnerability due to reduced adaptability, while younger farmers face high vulnerability linked to limited resources and experience [23]. Family size directly affects livelihood vulnerability, influencing dependency [24]. Households with 1–3 members showed low vulnerability; 3–5 members showed moderate to high; 7–10 members indicated high; and more than 10 members reported very high vulnerability.

The education level of farmers plays a significant role in improving their capacity to access and apply modern agricultural practices [24]. Those with no formal or only primary education were more vulnerable due to limited access to markets and agricultural information. Farmers with secondary education experienced lower vulnerability due to enhanced resource management and adaptive skills. Fertilizer cost (including N-P-K and supplementary nutrients) was used as a proxy for input investment and financial burden [25–27]. Farmers spending INR 5000–10,000 experienced low vulnerability, those spending INR 10,000–15,000 moderate vulnerability, and those with costs above INR 25,000 faced high vulnerability. Income from pulses per hectare is a critical livelihood component, reflecting diversification and resilience to rice crop failure [28]. While pulses remain in demand, farmer interest in their cultivation has recently declined [39]. About 58.27% of respondents experienced high vulnerability due to low income from pulses; 11.91% showed moderate vulnerability, while only 3.53% each reported low, very low, or negligible vulnerability.

3.3.2 Exposure

Exposure reflects the extent to which farmers' livelihoods are affected by external environmental and climatic stressors, particularly natural hazards and climate change [2].

The vulnerability of crops to weather and climate is a key factor, as erratic rainfall and heat extremes directly affect rice productivity. Climate-resilient farming practices and infrastructure development are needed to reduce this exposure [29–32]. Soil moisture during harvesting influences both yield and grain quality. Variability in moisture—whether too dry, too wet, or unstable—contributes to increased vulnerability [33, 44]. Pests, diseases, and weeds such as foot rot, stem rot, rice blast, leaf blight, and brown spot were reported as major threats, reducing crop yield and farmer income. Effective pest management strategies are essential [34, 45]. Access to critical weather information is vital for timely decision-making, influencing crop planning, irrigation scheduling, and pest control [35]. The Kharif season rainfall pattern also plays a significant role—moderate to high rainfall during harvest can lead to crop damage and income loss [36]. Similarly, high temperatures during the crop cycle can induce heat stress and reduce yields, especially during flowering and grain formation [37].

3.3.3 Sensitivity

Sensitivity refers to the degree to which farming outcomes are affected by fluctuations in environmental and institutional factors. These include access to resources, knowledge systems, and economic constraints [2].

The use of digital tools is increasingly important for precision farming and risk monitoring [38]. However, many farmers remain unaware of these technologies and require targeted training under current climate variability. Yield in tons/hectare is a critical livelihood indicator, directly reflecting productivity and financial stability [2]. Availability of quality pulse seeds, particularly in rice-fallow periods, is essential for cropping intensity and resilience [39]. Timely seed availability helps farmers mitigate pest attacks and weather-related delays. The frequency of practicing RFP (Rice-Fallow-Pulse) cultivation after Kharif reflects sustainable land use and resource efficiency [40]. This practice improves soil health, recycles nutrients, and enhances income security [39]. Its absence increases vulnerability. Soil problems, including salinity and hardpan layers, reduce productivity and pose serious livelihood risks [41]. Field surveys identified varying soil constraints and their impact on vulnerability levels. Lastly, the frequency of land left fallow post-Kharif influences weed dynamics, soil fertility, and long-term land sustainability [42]. Regular fallowing without planned rotations was associated with higher vulnerability.

4 Methods

The study's flow of methodological approaches is given (Fig. 2).

4.1 Multicollinearity analysis

Understanding how different factors relate to each other is crucial for making decisions, like predicting LVI. Sometimes, there's a statistical issue called multicollinearity, where two or more factors are strongly connected [40]. However, this doesn't mean our predictions are incorrect. Researchers use a tool called Variance Inflation Factor (VIF) to check for this strong relationship, which helps them make better decisions based on how factors are connected [46]. This method is used in many studies to analyze multiple factors and make informed decisions. We have applied the given (Eq. 1) to perform the multicollinearity analysis using linear regression with collinearity diagnostics in SPSS with the help of defined process field sample (1814) data layers (17) [46].

$$\begin{matrix} (T_i) = 1 - R_i^2 \\ (VIF_i) = \dfrac{1}{T_i} \end{matrix} \quad \begin{cases} T_i = Tolerance\, of\, the\, i^{th}\, predictor\, criterion \\ VIF_i = The\, variance\, inflation\, factor\, of\, the\, i^{th}\, predictor\, criterion \\ R^2 = The\, coefficient\, of\, determination\, of\, the\, regression\, equation \end{cases} \tag{1}$$

Initially, Nitrogen (N), Phosphorus (P), and Potassium (K) input costs were considered as separate variables. However, due to high intercorrelation (VIF > 10), these were aggregated into a single composite variable: Total NPK Cost. This transformation improved the model's fitness and reduced collinearity. We adopted a VIF threshold of 10 as the

Table 1 Distribution and nature of field-based adaptive capacity category conditioning factors for LVI and LVI-IPCC analysis

Category	Factors	Data range	Class value	Vulnerability level	Sample	Percentage	Weightage (Based on 1)		Crireria	Source
							Over all LVI	LVI-IPCC		
Adaptive capacity	Age of farmers	18–30	1	High	82	4.52	0.0555	0.1	NC	Field survey
		30–45	2	High to moderate	916	50.50				
		45–60	4	Low	702	38.70				
		60 above	3	Moderate	114	6.28				
	Number of family member in a farmer's household	1–3	1	Low	218	12.02	0.065	0.2	BC	Field survey
		3–5	2	Moderate	1377	75.91				
		5–7	3	Moderate to high	131	7.22				
		7–10	4	High	80	4.41				
		10 above	5	Very high	8	0.44				
	Education level of farmers	No Schooling	1	Very high	172	9.49	0.0565	0.15	NC	Field survey
		Primary	2	High	667	36.77				
		Secondary	3	High to moderate	656	36.16				
		Higher Secondary	4	Moderate	229	12.62				
		Under graduate	5	Moderate to low	82	4.52				
		Post graduate and above	6	Low	8	0.44				
	Cost of fertilizers (N-P-K and Supplementary Nutrients)	Up to 5000	1	Low	764	42.12	0.069	0.3	BC	Field Survey
		5000–10,000	2	Low to moderate	195	10.75				
		10,000–15,000	3	Moderate	118	6.50				
		15,000–20,000	4	Moderate to high	218	12.02				
		20,000–25,000	5	High	323	17.81				
		25,000 above	6	Very high	196	10.80				
	Income from Pulses/Hectare	Up to 10,000	1	Very high	1057	58.27	0.067	0.25	NB	Field survey
		10,000–20,000	2	High	477	26.29				
		20,000–30,000	3	Moderate	216	11.91				
		30,000 above	4	Low	64	3.53				
		Sometimes	2	Moderate	1237	68.19				
		Alternative years	3	High	28	1.55				

BC, Beneficial Criteria (If, highest class value indicates high vulnerability and lowest class value indicates low vulnerability); NC, Non-Beneficial Criteria (If, lowest class value indicates high vulnerability and highest class value indicates high vulnerability)

Table 2 Distribution and nature of field-based exposure category conditioning factors for LVI and LVI-IPCC analysis

Category	Factors	Data range	Class value	Vulnerability level	Sample	Percentage	Weightage (Based on 1)		Crireria	Source
							Over all LVI	LVI-IPCC		
Exposure	Crop's vulnerability to weather/climate	High vulnerable	1	High	21	1.16	0.0585	0.19	NC	Field survey
		Medium vulnerable	2	Moderate	1188	65.49				
		Low vulnerable	3	Low	605	33.35				
	Soil moisture status during harvesting	High	1	High	15	0.83	0.059	0.09	NC	Field survey
		Dry	2	High to moderate	524	28.89				
		Low	3	Moderate	209	11.52				
		Medium	4	Low	1066	58.76				
	Main pest, disease and weed	Foot rot or bakanae disease	1	High	121	6.67	0.063	0.29	NC	Field survey
		Stem rot	1	High	41	2.26				
		Rice blast	1	High	463	25.52				
		Leaf blight	2	High to moderate	537	29.60				
		Brown spot	2	High to moderate	376	20.73				
		Tungro disease	3	Moderate	276	15.22				
	Critical weather information	Rainfall intensity and drought spells	1	High	652	35.94	0.0575	0.24	NC	Field survey
		Wind speed and relative humidity	2	Moderate	590	32.53				
		Temperature, heat waves and other	3	Low	572	31.53				
	Temperature	17.30–18.00 °C	1	Low	223	12.29	0.054	0.05	BC	CRU
		18.00–19.00 °C	2	Moderate	1314	72.44				
		Above 19.00 °C	3	High	277	15.27				
	Rainfall	1800–2000 mm	1	Low	887	48.90	0.061	0.14	BC	CHRS PERSIANN-CCS
		1600–1800 mm	2	Moderate	268	14.77				
		Above 2000 mm	3	High	659	36.33				
		Sometimes	2	Moderate	1237	68.19				
		Alternative years	3	High	28	1.55				

Temperature Source: https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.07/cruts.2304141047.v4.07/tmp/

Rainfall Source: https://chrsdata.eng.uci.edu/

upper acceptable limit. After this adjustment, all variables were retained, and none exceeded the defined threshold, ensuring a stable input dataset for EDAS modeling.

4.2 LVI using EDAS model

The newly proposed and one of the most prominent MCDM techniques is EDAS (Evaluation based on Distance from Average answer) [46]. The EDAS model is a decision-making tool that ranks alternatives according to their proximity to the average answer. EDAS determines the Euclidean distance of each alternative from the average answer in multi-criteria decision-making (MCDM). The closer an alternative is to the average solution, the higher its rank [47]. This model was selected over methods like TOPSIS, VIKOR or AHP due to its ability to reduce subjectivity in weight assignments and its alignment with non-compensatory logic in vulnerability analysis. Additionally, based on expert consultation, EDAS was considered particularly effective for handling field-derived, multi-structure datasets-such as the combination of socio-economic, environmental, and perception-based variables used in this study-due to its capacity to preserve the individual character of each criterion without over-compensating between extremes. A sample performance matrix and calculation workflow is now provided in the Supplementary File to increase methodological transparency. The authors computed the model based on the surveyed data. This method aids in selecting the most suitable option from a set of alternatives by considering their distances from the mean solution. In this study, the Livelihood Vulnerability Index (LVI) is developed using the EDAS model to assess and rank the vulnerability of livelihoods in each area. By applying the EDAS method to 17 indicators such as age of farmers, number of family members in a farmer's household, education level of farmers, cost of fertilizers (N-P-K and supplementary nutrients, income from pulses/hectare, crop's vulnerability to weather/climate, soil moisture status during harvesting, main pest, disease and weed, critical weather information, rainfall, temperature, utilization of digital tools, yield in tons/hectare, availability of rice fallow pulse seeds, how often RFP is followed after Kharif, soil problems in farmer's plot, and how often kept land fallow after Kharif. The LVI provides a numerical measure of livelihood vulnerability. The EDAS model calculates the distance of each livelihood indicator from the average, helping to identify which livelihoods are most vulnerable and in need of targeted interventions. This approach enables policymakers and organizations to prioritize resources and interventions to improve the resilience of vulnerable livelihoods. The ranking or weightage of each factor is decided by a concrete discussion with farmers and experts in this field. The study applied the given steps to computing the model [47].

Step I: The constraints of the initial decision matrix are based on real-field-based processed data layers on a qualitative scale. For the decision matrix, compute n ($n = 1,2\ldots,j$) criteria and m alternative ($m = 1,2,\ldots,i$) as follows, given Eq. 2.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{xm} \end{bmatrix} \tag{2}$$

Table 3 Distribution and nature of field-based sensitivity category conditioning factors for LVI and LVI-IPCC analysis

Category	Factors	Data range	Class value	Vulnerability level	Sample	Percentage	Weightage (Based on 1)		Crireria	Source
							Over all LVI	LVI-IPCC		
Sensitivity	Utilization of digital tools	Never and unaware	1	Very high	321	17.70	0.058	0.14	NC	Field survey
		Needs training	2	High	552	30.43				
		Sometimes	3	Moderate	935	51.54				
		Often	4	Low	6	0.33				
	Yield in tons/hectare	Up to 5	1	Very high	1492	82.25	0.075	0.29	NC	Field survey
		5–10	2	Moderate	290	15.99				
		10–15	3	Moderate to low	26	1.43				
		15 above	4	Low	6	0.33				
	Availability of rice fallow pulse seeds	Available	1	Low	1271	70.07	0.042	0.05	BC	Field survey
		Sometimes	2	Moderate	465	25.63				
		Rarely	3	High	8	0.44				
		Unavailable	4	Very high	70	3.86				
	How often RFP is followed after Kharif	Annually	1	Low	113	6.23	0.047	0.19	BC	Field survey
		Alternate years	2	Moderate	323	17.81				
		Sometimes	3	High	1235	68.08				
		Rarely	4	Very high	143	7.88				
	Soil problems in Farmer's Plot	Hardpan	1	Very high	24	1.32	0.06	0.24	NC	Field survey
		Heavy metal	2	High	176	9.70				
		Salinity	3	Moderate to high	499	27.51				
		Sodicity	4	Moderate	125	6.89				
		Nothing	5	Low	990	54.58				
	How often kept land fallow after Kharif	Never	1	Low	549	30.26	0.052	0.09	BC	Field survey
		Sometimes	2	Moderate	1237	68.19				
		Alternative years	3	High	28	1.55				

Hence, x_{ij} denote the performance value of the alternative i^{th} on j^{th} criterion by w_j, Represent $0 < w_j < 1\, and\, \sum_{j=1}^{m} w_j = 1$.

For the method construction the study follows the given steps.

Step I: Performed the average solution (v_j) using the given (Eq. 3) for every criterion.

$$v_j = \frac{\sum_{i=1}^{n} x_{ij}}{n} \tag{3}$$

Step II: Pd_{ij} and Nd_{ij}determine by given (Eq. 4 and Eq. 5)

$$Pd_{ij} = \begin{cases} \frac{max(0, x_{ij} - v)}{v_j} if\, j \in BC \\ \frac{max(0, v_j - x_{ij})}{v_j} if\, j \in NC \end{cases} \tag{4}$$

$$Nd_{ij} = \begin{cases} \frac{max(0, v_j - x_{ij})}{v_j} if\, j \in BC \\ \frac{max(0, x_{ij} - v_j)}{v_j} if\, j \in NC \end{cases} \tag{5}$$

Hence, Pd_{ij} and Nd_{ij} denotes to positive and negative distance from the average solution respectively. Where, *BC* and *NC* means beneficial and non-beneficial criterion respectively.

Step III: Performing the weighted summation of Pd_{ij} and Nd_{ij} by the (Eq. 6 and Eq. 7)

$$SP_i = \sum_{j=1}^{m} w_j Pd_{ij} \tag{6}$$

$$SN_i = \sum_{j=1}^{m} w_j Nd_{ij} \tag{7}$$

Step IV: Performing SP_i and SN_i normalization by the (Eq. 8 and Eq. 9)

$$NSP_i = \frac{SP_i}{\underset{k}{max} SP_k} \tag{8}$$

$$NSN_i = 1 - \frac{SN_i}{\underset{k}{max} P_k} \tag{9}$$

Step V: Calculation of appraisal score (AS_i) for every alternative follows the (Eq. 10)

$$AS_i = \frac{1}{2}(NSP_i + NSN_i) \tag{10}$$

Step VI: At last, alternatives are ranked based on the decreasing values of AS_i.

4.3 LVI-IPCC

The LVI-IPCC (Livelihood Vulnerability Index under the Intergovernmental Panel on Climate Change Conditions) categorizes vulnerability into three different angles, adaptive capacity, sensitivity, and exposure [7, 48]. This approach involves grouping the 17 factors into three categories (adaptive capacity, sensitivity, and exposure), where adaptive capacity is influenced by factors related to socio-demographic factors, social networks, and livelihood strategies [2], such as, for example, the age of farmers, the number

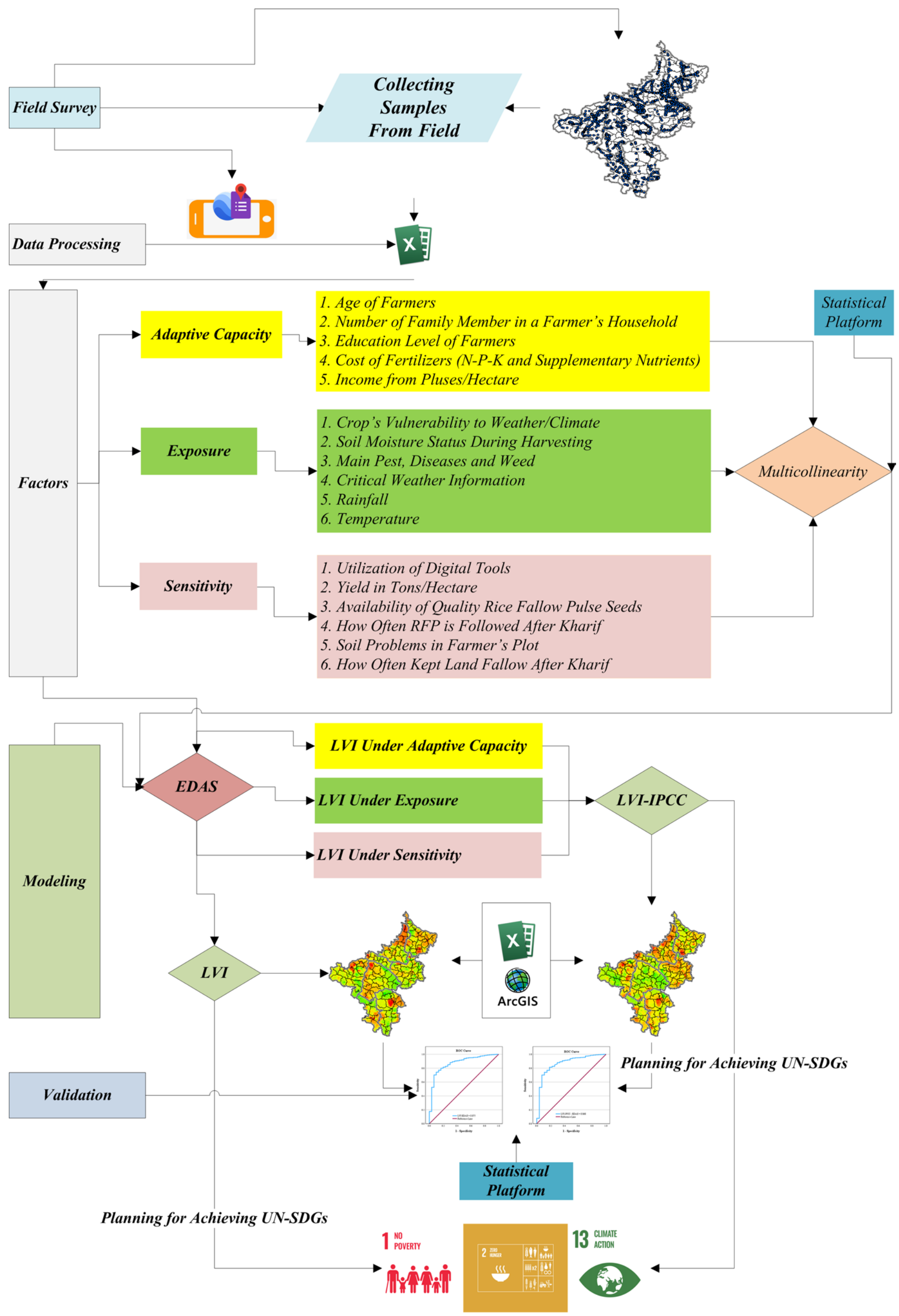


Fig. 2 Overall methodological framework

of family members in a farmer's household, the education level of farmers, the cost of fertilizers (N-P-K and supplementary nutrients), and income from pulses/hectare. Sensitivity encompasses things related to knowledge, natural resources, and finances [2], such as, for example, the utilization of digital tools, yield in tons/hectare, the availability of rice fallow pulse seeds, how often RFP is followed after Kharif, soil problems in farmer's plots, and how often kept land fallow after Kharif. While exposure considers the factors related to the effects of natural disasters and climate change impacts [2], such as, for example, a crop's vulnerability to weather/climate, soil moisture status during harvesting, main pests, diseases and weeds, critical weather information, rainfall, and temperature. The specific subcomponents of these categories are detailed in Tables 1 and 2, and 3 which are utilized to calculate the combined contributing factors of the main components. The EDAS model has been applied to every angle of LVI calibration (Eqs. 2,3,...,10). After that, the LVI-IPCC is calculated using the given Eq. 11 [2, 49].

$$LVI - IPCC = (E_x - A_c) \times S_n \begin{cases} E_x = Exposure \\ A_c = Adaptive\,Capacity \\ S_n = Sensitivity \end{cases} \tag{11}$$

Value range differ from – 1 (Least Vulnerable) to + 1 (Most Vulnerable) [2].

4.4 Validation

The study applied ROC-AUC for validation purposes. ROC-AUC (area under the curve of receiver operating characteristic)techniques always measure classification accuracy [40]. The authors applied the techniques to validate the EDAS model using Eq. 12 [46].

$$\begin{cases} x = 1 - S_p \\ y = S_n \end{cases} \tag{12}$$

$$\begin{cases} S_p = 1 - \left(\dfrac{TN}{TN + FN}\right) \\ S_n = \dfrac{TN}{TP + FN} \end{cases} \tag{13}$$

Where, S_p and S_n refer to specificity and sensitivity, respectively. In the specificity and sensitivity equations (Eq. 13) *TN* means true negative, *TP* means true positive, *FN* means false negative, and *FP* is false positive.

5 Results

5.1 Field based conditioning factors

5.1.1 Adaptive capacity

The adaptive capacity of pulse-growing communities remains significantly constrained due to socio-economic and infrastructural limitations. Although 50.50% of the farmers are within the productive age group (30–45 years), and 38.70% between 45 and 60, field insights from Bankura, Jhargram, and Purulia reveal limited preparedness to deal with seasonal challenges. In Bankura, uneven terrain and poor irrigation facilities hamper the timely preparation of fields and efficient water management. Farmers here reported insufficient training and limited access to crop-specific advisories, especially for short-duration pulses that require precise sowing and drainage. Jhargram faces acute labour shortages during peak field preparation periods, which delays operations and impacts productivity. In Purulia, issues like low soil fertility and restricted access to essential inputs limit farmers' ability to adopt improved cropping strategies. Quantitative indicators support these observations. Households with 1–3 members showed lower vulnerability (12.02%), while medium-sized families (3–5 members) faced greater challenges (75.91%). Income-related vulnerability is also pronounced-58.27% of respondents with net returns between INR 10,000 and 20,000 per hectare reported high levels of livelihood stress. A lack of formal education (9.49% with no schooling) and limited budgetary capacity further diminish the ability of farmers to respond effectively to emerging risks.

These constraints clearly reflect the systemic gaps that undermine adaptability in pulse-based farming systems.

5.1.2 Exposure

Climatic variability significantly increases exposure risk, particularly due to irregular rainfall patterns, temperature fluctuations, and disease outbreaks. While 1.16% of cropped areas were classified as highly vulnerable, 65.49% were moderately affected, and 33.35% experienced lower levels of stress. Field visits in Purba Bardhaman and Paschim Medinipur showed instances of excessive precipitation leading to waterlogging and submergence in low-lying plots. In contrast, Bankura and Birbhum experienced rainfall deficits during critical planting windows, resulting in poor germination and reduced crop stands. Delayed monsoon onset in Jhargram similarly affected field operations, while early-season heat stress in Paschim Bardhaman compromised seedling survival. Common diseases such as foot rot, stem rot, and leaf blight were widely reported in moisture-stressed areas. Additionally, 35.43% of farmers expressed high sensitivity to weather anomalies, while 32.53% cited wind and humidity as key disruptive elements. Nearly half of the respondents indicated moderate to high rainfall-related vulnerability, particularly those engaged in rainfed pulse production. These observations confirm that exposure is closely tied to spatial variability in weather and limited agroecological resilience.

5.1.3 Sensitivity

Production systems remain highly sensitive to multiple stressors, including limited market access, rising input costs, and infrastructural weaknesses. Survey data show that 17.70% of respondents were unaware of digital tools, while 30.43% required training to use them effectively. Although 51.54% accessed digital services occasionally, inconsistent usage reflects information asymmetry and poor institutional support. Field-based reports from Birbhum and Bankura reveal that high initial investment in seeds, fertilizers, and labour deters many from taking up pulse cultivation. The situation is exacerbated during peak rainfall months, when incomes are low and transportation becomes more difficult. Poor rural connectivity affects the ability to reach procurement centres, especially in Purulia and Paschim Bardhaman, leading to low profit margins even in seasons with satisfactory yields. The majority of respondents (82.25%) reported yields below 5 tons per hectare, reinforcing production-level vulnerability. Soil degradation due to salinity (27.51%), contamination (9.70%), and poor structure (6.89%) further affects productivity. Labour shortages during critical weeding and harvesting periods increase dependency on wage labour, adding financial pressure. Inconsistent land management practices—such as fallowing-were also noted, with only a minority maintaining regular soil-rest periods. These compounded stressors underline the systemic sensitivity embedded in rain-dependent agriculture.

5.2 Multicollinearity analysis

Multicollinearity analysis was conducted by statistical software, and the result is shown in Table 4. The analysis revealed that the highest variance inflation factor (VIF) observed for 'cost of fertilizers 'N-P-K and supplementary nutrients' (VIF = 4.357, tolerance = 0.229), indicating a potential influence on other factors. Conversely, the lowest values were found for 'number of family members in a farmer's household' (VIF = 1.080,

Table 4 Multicollinearity statistics

Factors	Collinearity statistics	
	Tolerance	VIF
Number of Family Member in a Farmer's Household	0.926	1.080
Cost of Fertilizers (N-P-K and Supplementary Nutrients)	0.229	4.357
Age of Farmers	0.875	1.143
Education Level of Farmers	0.797	1.255
Income from Pulses/Hectare	0.517	1.936
Rainfall	0.770	1.299
Temperature	0.867	1.154
Crop's Vulnerability to Weather/Climate	0.440	2.272
Soil Moisture Status During Harvesting	0.477	2.094
Main Pest, Disease, and Weed	0.783	1.278
Critical Weather Information	0.411	2.432
Availability of Rice Fallow Pulse Seeds	0.792	1.263
How often RFP is followed After Kharif	0.716	1.397
How Often Kept Land Fallow After Kharif	0.426	2.346
Utilization of Digital Tools	0.498	2.010
Yield in Tons/Hectare	0.738	1.355
Soil problems in Farmer's Plot	0.512	1.955

tolerance = 0.926) and 'age of farmers' (VIF = 1.143, tolerance = 0.875), respectively. The VIF values were all below the threshold of 10, indicating that no significant collinearity occurred between the factors [40]. This suggests that all the factors can contribute meaningfully to the modeling process with the chosen equation. In the context of the study, field data (except rainfall and temperature) was utilized to predict LVI and LVI-IPCC, particularly in Jhargram, Paschim Medinipur, Bankura, Purulia, PurbaBardhaman, Paschim Bardhaman, Birbhum, and Murshidabad, based on Excel and GISplatform. Subsequently, sample-based modeling techniques like EDAS were employed to predict LVI and LVI-IPCC.

5.3 LVI

In this study, sample data from several districts in West Bengal were used to generate the LVI using EDAS. LVI analysis takes into account both quality and quantity of agricultural data. The EDAS approach under discussion is not pixel-based, hence sample coordinates were used in this research [47]. The assessment matrix for the EDAS was created in Excel by processing field data for each factor ($n = 17$). Table ST. 3 depicts the EDAS technique's assessment matrix, which includes 1814 rows (samples) and 17 columns (factors). It was built around the category and weights assigned to the conditioning factors. Weight determination for LVI conditioning factors is an important challenge in this regard. The weights of the criteria are determined by consulting with local farmers and professionals in the field, as stated in Tables 1, 2 and 3 and ST2-ST4. Seven of the 17 factors were identified as advantageous (*BC*), with ten criteria classed as non-beneficial (*NC*). In this approach, the outcome value (*ASi*) ranges from 0 to 1, where 0 represents the least vulnerable and 1 represents the most vulnerable [46, 47]. The final *ASi* score of EDAS is calculated by adding *NSPi* and *NSNi*, which indicate positive and negative EDAS [46]. The highest *NSPi* value is 0.99, while the lowest is 0.07 (Fig. SF4).

On the other side, the greatest *NSNi* value is 0.90, while the lowest is extremely near to 0. The model's *ASi* value is 0.17–0.94, while the concentration value ranges from 0.30 to 0.89, indicating that the study area has a high level of susceptibility (Fig. 4A). The

LVI result was confirmed by ROC-ACU using ground data (farmers' opinions), and a value of 0.874 suggests that the model is successful in predicting major acceptable areas (Fig. 4A). Climate sensitivity, strong reliance on agriculture, water management issues, and socioeconomic inequities are all contributing factors to this susceptibility [2]. To alleviate these risks, targeted actions are required, such as encouraging climate-resilient farming techniques, improving water resource management, and addressing socioeconomic inequities to strengthen farmers' resilience in these regions.

5.4 LVI-IPCC

In this research, for LVI-IPCC computing, the EDAS model was applied with three different categories: EDAS for adaptive capacity, EDAS for exposure, and EDAS for sensitivity. The adaptive capacity of the study area was assessed based on five different factors and exposure (6), and sensitivity was assessed based on 6 different factors as well. EDAS for every category is performed by calculating *NSPi* and *NSNi*, which indicate positive and negative EDAS [38]. Every category *ASi* indicates the category's ultimate LVI value. According to the model, a larger *ASi* number suggests greater risk, whereas a lower one indicates less vulnerability. The highest *NSPi* and *NSNi* values (very near to 1) are recorded in three categories, while the lowest values (very close to 0) are also observed in all three categories, indicating that a variable level of vulnerability may exist in the study area (Fig. SF4).

The AS_i value of the adaptive capacity category is 0.09–0.97, and the concentrate value ranges from 0.40 to 0.98, which indicates a moderate to high vulnerability level exists for controlling all adoptive capacity factors (Fig. 3A). The AS_i value of the exposure category is 0.01–0.99. It expresses somewhere exposure-based factors like 'crop's vulnerability to weather/climate, soil moisture status during harvesting, main pests, diseases, and weeds, critical weather information, rainfall, and temperature conditions are adopted by farmers, and some where adverse situations are occurring. The concentration value ranges from 0.21 to 0.88, indicating a significant disparity in the factorial management of the exposure category across the majority of the area (Fig. 3B). The AS_i value of the sensitivity capacity category is 0.00–0.99, and the concentrate value ranges from 0.22 to 0.89, which indicates a moderate to very high vulnerability level exists for controlling all adoptive capacity factors (Fig. 3C). The study found that the LVI-IPCC value ranged from − 0.48 to 0.54. The value of 0.54 indicates a higher vulnerability level (closer to + 1), suggesting farmers are more susceptible to climate and environmental changes (Fig. 4B). Conversely, the value of -0.48 indicates a lower vulnerability level (closer to -1), meaning farmers are relatively less vulnerable to such changes. The LVI-IPCC result was validated by ROC-ACU based on ground data (farmers opinions), and the value of 0.868 indicates that the model is successful in significant area prediction (Fig. 4B).

6 Discussions

To gain a comprehensive understanding of the agricultural livelihoods of rice farmers in West Bengal, this study analyzes the Livelihood Vulnerability Index (LVI) and LVI-IPCC, which are critical for informing management planning, policy development, and alignment with the United Nations Sustainable Development Goals (SDGs) [1, 2, 23, 24, 31, 37, 50– [52]. By integrating statistical modeling with geospatial techniques, our research provides enhanced visibility into categorized vulnerable zones, enabling targeted

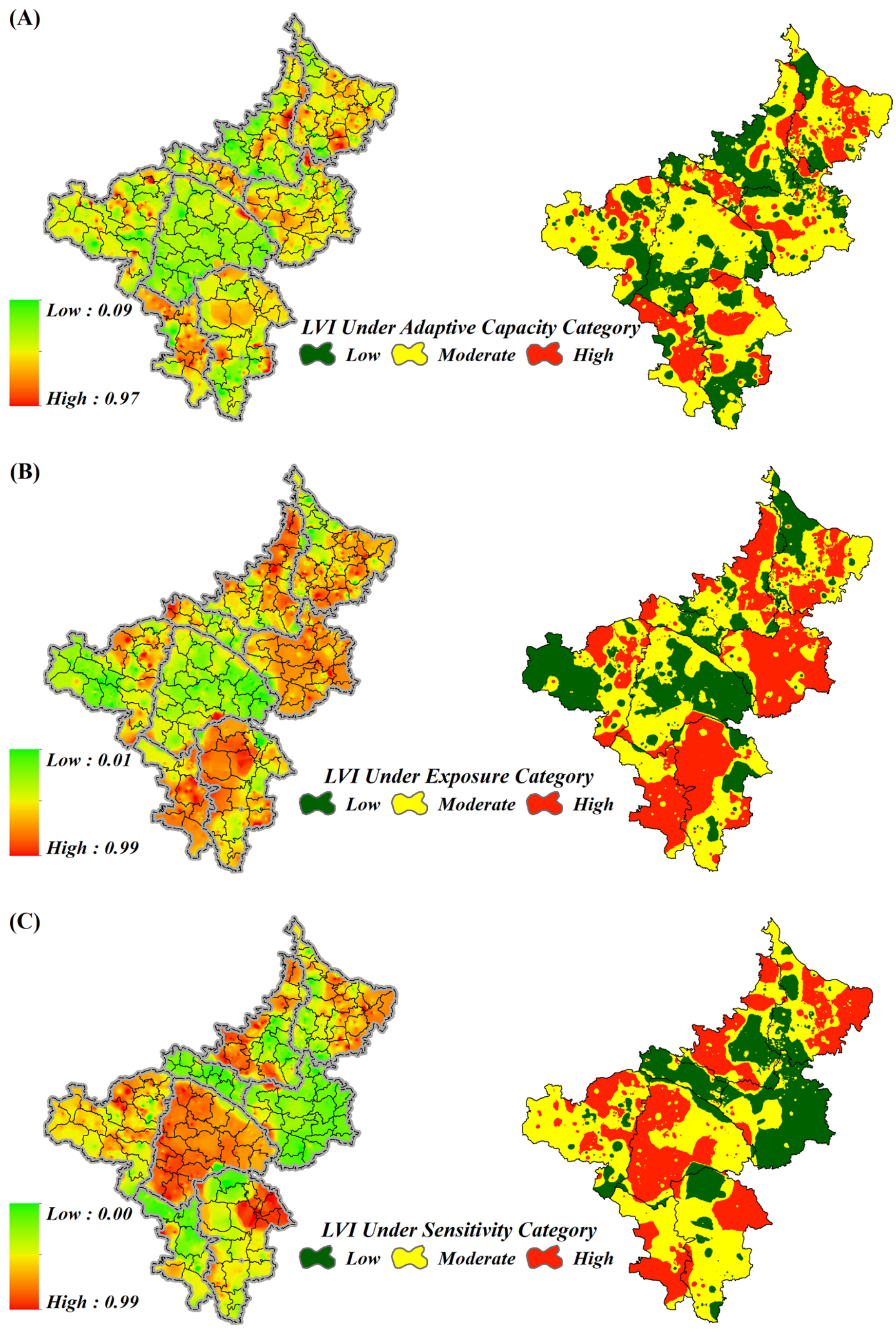


Fig. 3 Representation of category-wise LVI maps of the study area

problem-solving decisions, addressing a gap in spatially explicit, field-based vulnerability assessments [46]. Below, we critically evaluate how our findings confirm, contradict, or expand upon prior studies, particularly those by Singh et al. [52] and Tran et al. [2], articulate the novelty of our EDAS-based LVI-IPCC methodology, discuss implications for local governance, and propose site-specific interventions to enhance resilience and sustainability.

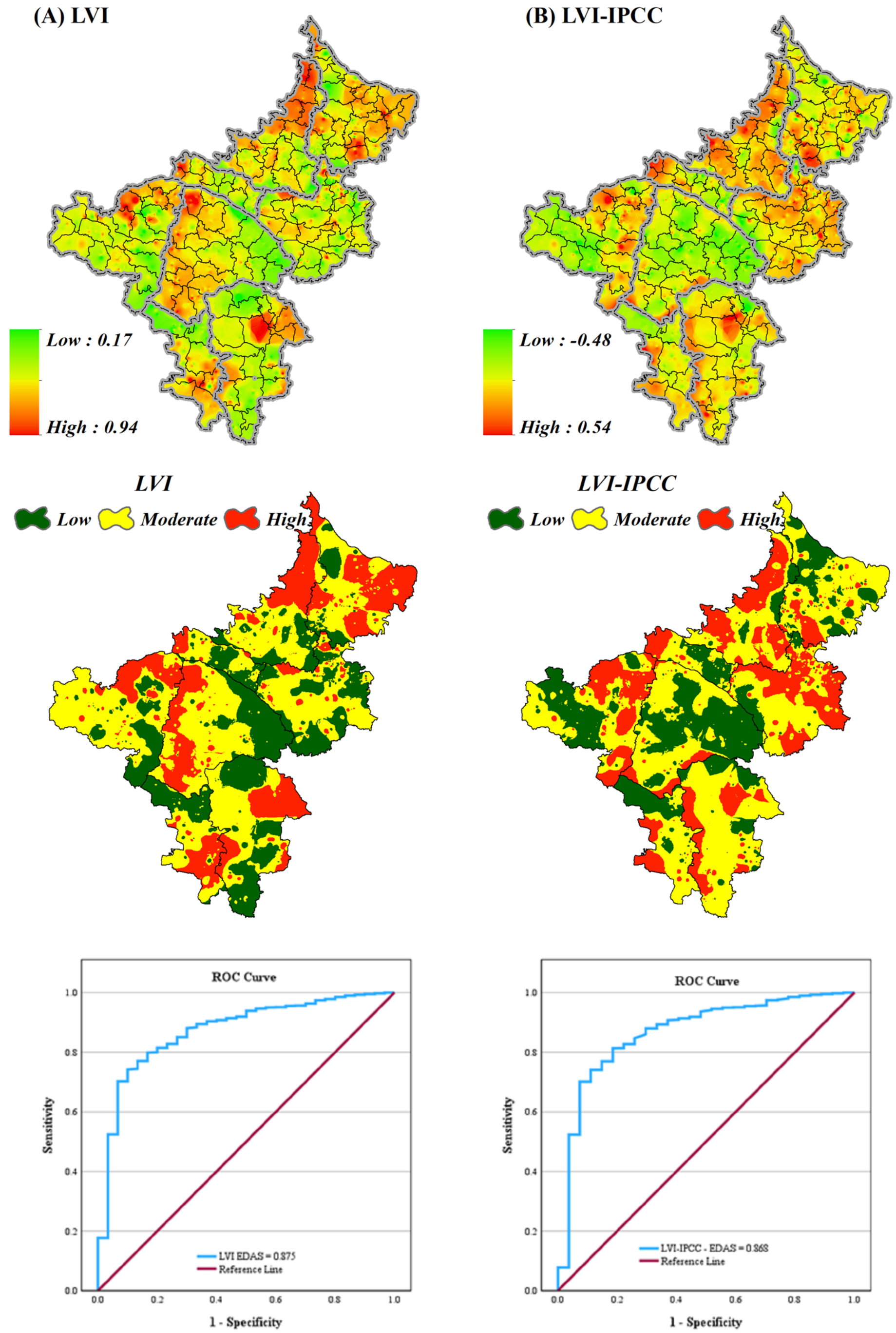


Fig. 4 Representation of LVI and LVI-IPCC map with validation curve

6.1 Comparative analysis with prior studies

Singh et al. [52] assessed climate suitability changes for rainfed rice in India, projecting that 15–40% of current areas are at risk by 2050 due to climate variability. Their study employed statistical models to map spatial suitability, emphasizing the need for drought-resilient rice varieties and improved irrigation. Our findings confirm their observation of significant climate-related risks, particularly in districts like Birbhum (32.88% high LVI area) and Murshidabad (48.16% high LVI area), where exposure to erratic rainfall and temperature fluctuations (Table 5; Fig. 4A) aligns with their projected vulnerabilities

Table 5 District-wise, different categories' vulnerable areas (%)

Vulnerability category	Vulnerability level	Jhargram	Paschim Medinipur	Bankura	Purulia	PurbaBardhaman	Paschim Bardhaman	Birbhum	Murshidabad
LVI	High	27.86	25.04	23.56	19.09	07.43	15.32	32.88	48.16
	Moderate	37.78	38.52	49.73	58.42	53.67	45.62	45.95	38.88
	Low	34.35	36.44	26.71	22.48	38.90	39.06	21.17	12.96
LVI-AC	High	53.09	24.03	04.93	14.31	19.21	32.80	13.32	30.89
	Moderate	38.95	50.13	62.41	59.98	59.67	34.25	41.04	50.60
	Low	7.95	25.83	32.66	25.63	21.12	32.95	45.63	18.51
LVI-E	High	62.88	49.34	05.7	23.29	72.85	16.09	41.63	29.29
	Moderate	35.74	35.18	46.06	31.15	23.93	51.28	39.66	44.84
	Low	1.37	15.48	48.24	45.75	03.23	32.62	18.71	25.87
LVI-S	High	43.87	25.24	51.42	27.69	05.24	03.09	43.18	41.40
	Moderate	55.92	56.56	39.96	61.85	23.73	17.63	28.66	38.39
	Low	00.21	18.20	08.61	10.46	71.03	79.28	28.16	20.21
LVI-IPCC	High	17.22	21.58	06.97	31.98	46.13	23.6	46.95	11.71
	Moderate	51.28	64.05	42.72	37.64	44.53	37.41	42.85	59.61
	Low	31.50	14.37	50.29	30.37	09.34	38.98	10.19	28.68

LVI, Livelihood vulnerability index; AC, Adaptive capacity; E, Exposure; S, Sensitivity; IPCC, Intergovernmental panel on climate change

[52]. However, our LVI-IPCC approach outperforms their methodology by integrating 17 field-based indicators (Tables 1, 2 and 3) within the IPCC framework, enabling a granular assessment of adaptive capacity, exposure, and sensitivity. Unlike Singh et al.'s climate-focused models, our study quantifies socio-economic drivers (e.g., education level, fertilizer costs) and their spatial distribution, revealing that Jhargram's high adaptive capacity vulnerability (53.09%, Table 5) stems from limited education and income. This multidimensional perspective provides a more holistic vulnerability profile, facilitating precise intervention priorities, such as promoting climate-smart agriculture in Birbhum and Murshidabad. Tran et al. [2] evaluated livelihood vulnerability in the Vietnam Mekong Delta (VMD), focusing on rice farmers' adaptations to climate change and environmental pressures. Their study used the LVI-IPCC framework but relied heavily on qualitative stakeholder inputs, limiting quantitative precision. Our findings partially contradict their assertion of uniformly low adaptive capacity in flood-prone areas, as we observed significant variation across West Bengal districts (e.g., Purba Bardhaman at 19.21% high LVI-AC vs. Jhargram at 53.09%, Table 5). Our EDAS-based LVI-IPCC model enhances Tran et al.'s approach by integrating quantitative data from 1814 farmers with geospatial analysis (Fig. 3A–C), achieving higher statistical robustness (ROC-AUC = 0.86 for LVI-IPCC, Fig. 4B). For instance, Purba Bardhaman's high exposure (72.85%, Table 5) due to heavy rainfall and soil moisture issues (Fig. 5K) necessitates targeted interventions like improved drainage systems, which our spatially explicit model identifies more effectively than Tran et al.'s qualitative focus [2]. This quantitative-geospatial integration expands the LVI-IPCC's applicability, offering a scalable model for diverse agro-ecological contexts. Our study also builds on works like Zhao et al. (2019) [8], who used the Livelihood Capital Index in Tibet, and Wassie et al. [9], who assessed drought-induced vulnerabilities in Ethiopia. These studies provide valuable insights but lack the geospatial granularity and IPCC-aligned standardization of our approach. Mekonen & Berlie, (2021) study evaluates rural households' climate vulnerability in the Northeastern Highlands of Ethiopia, prioritizing exposure, sensitivity, and adaptive capacity [37]. Our study also focuses on the different approaches and geospatial techniques applied to better understand these approaches. The EDAS model's ranking of vulnerability based on distance from average solutions offers a methodological advancement over traditional MCDM methods like TOPSIS by reducing subjectivity in weight assignment [46, 47], positioning our study as a robust tool for policymakers.

6.2 Implications of findings

The high vulnerability in districts like Jhargram, Birbhum, and Murshidabad (27.86–48.16% high LVI areas, Table 5) reflects a combination of climate sensitivity, heavy reliance on agriculture, water management challenges, and socio-economic inequities [2]. For instance, Purba Bardhaman's high exposure (72.85%, Table 5) due to heavy rainfall and inadequate drainage (Fig. 5K) poses significant risks to crop yields and livelihoods, requiring interventions like embankment strengthening and climate-resilient crop calendars (Sect. 8.2). This high exposure could disrupt local food security and exacerbate poverty unless addressed through targeted governance actions, such as infrastructure investments. Conversely, Paschim Bardhaman's lower vulnerability (15.32% high LVI, Table 5) benefits from its mixed economic profile, suggesting that livelihood diversification could mitigate risks in more vulnerable districts [23]. These district-specific insights

Fig. 5 Photographs of different vulnerable angles taken from the field survey

guide local governance in prioritizing resources, such as educational programs in Jhargram to address low adaptive capacity (53.09%, Table 5) driven by limited education and income.

6.3 Alignment with UN-SDGs

This study supports SDGs 1 (No Poverty), 2 (Zero Hunger), 3 (Good Health and Well-being), 8 (Decent Work and Economic Growth), and 13 (Climate Action) by identifying vulnerability hotspots and proposing actionable interventions (Table 5; Fig. 4A-B). For SDG 1, addressing high vulnerability in Birbhum and Murshidabad through income diversification (e.g., promoting pulse cultivation, can reduce poverty. For SDG 2, improving yields in Bankura and Jhargram via soil health programs mitigates food insecurity. SDG 3 is supported by reducing health risks from environmental stressors, such as salinity in Purba Bardhaman (Fig. 5I). SDG 8 benefits from labor efficiency improvements through mechanization, while SDG 13 is advanced by climate-resilient practices like water-saving technologies. These interventions provide a roadmap for policymakers to enhance rural livelihoods and align with global sustainability goals.

6.4 Novelty and policy relevance

The novelty of this study lies in its integration of the EDAS model with LVI-IPCC, supported by extensive field data (1814 samples) and geospatial techniques. Unlike previous studies [2, 52], our approach combines quantitative rigor (ROC-AUC = 0.874 for LVI, Fig. 4A) with spatial visualization (Fig. 3A–C), enabling precise identification of vulnerability hotspots. The use of 17 field-based indicators (Tables 1, 2 and 3) captures socio-economic and environmental dimensions, offering a holistic assessment. This framework is scalable and adaptable, with potential applications in other climate-vulnerable regions [46, 53–55]. For policymakers, the study provides evidence-based insights to prioritize interventions, such as agro-tech hubs in Jhargram to address low digital tool adoption (17.70% unaware, Table 3) or drainage improvements in Purba Bardhaman to mitigate high exposure. Based on district-specific vulnerabilities in West Bengal, targeted interventions are recommended. Jhargram (53.09% high LVI-AC, 62.88% high LVI-E) requires digital literacy programs and agro-tech hubs to address low digital tool adoption (51.54% moderate use, Table 3), low-interest loans to enhance adaptive capacity, and embankment strengthening to mitigate heavy rainfall exposure (Fig. 5K). For Birbhum (32.88% high LVI, 46.95% high LVI-IPCC), promoting climate-resilient rice varieties and irrigation improvements is needed to counter high climate sensitivity (43.18% high LVI-S, Table 5), alongside farmer cooperatives for bulk fertilizer procurement (Table 1). Murshidabad (48.16% high LVI) should enhance market linkages and implement intelligence systems to improve pulse income (58.27% high vulnerability, Table 1), plus develop weather early warning systems to reduce exposure (29.29% high LVI-E, Table 5). Purba Bardhaman (72.85% high LVI-E) necessitates drainage investments and sustainable land planning to address heavy rainfall/salinity exposure (Fig. 5I and K), and organic fertilizers for soil health (27.51% salinity, Table 3). Paschim Bardhaman (15.32% high LVI) can leverage its mixed economy for livelihood diversification and support mechanization (Sect. 8.3). Bankura (51.42% high LVI-S) requires soil testing programs and incentives for sustainable management (Table 3), plus RFP cultivation promotion (6.23% annual RFP, Table 3). Purulia (31.98% high LVI-IPCC) needs rainwater harvesting for erratic rainfall exposure (Table 2) and financial incentives for climate-resilient practices (14.31% high LVI-AC, Table 5). Finally, Paschim Medinipur (25.04% high LVI) should establish community transport for market access (26.29% pulse vulnerability, Table 1) and promote climate-smart crop calendars to reduce exposure (49.34% high LVI-E, Table 5).

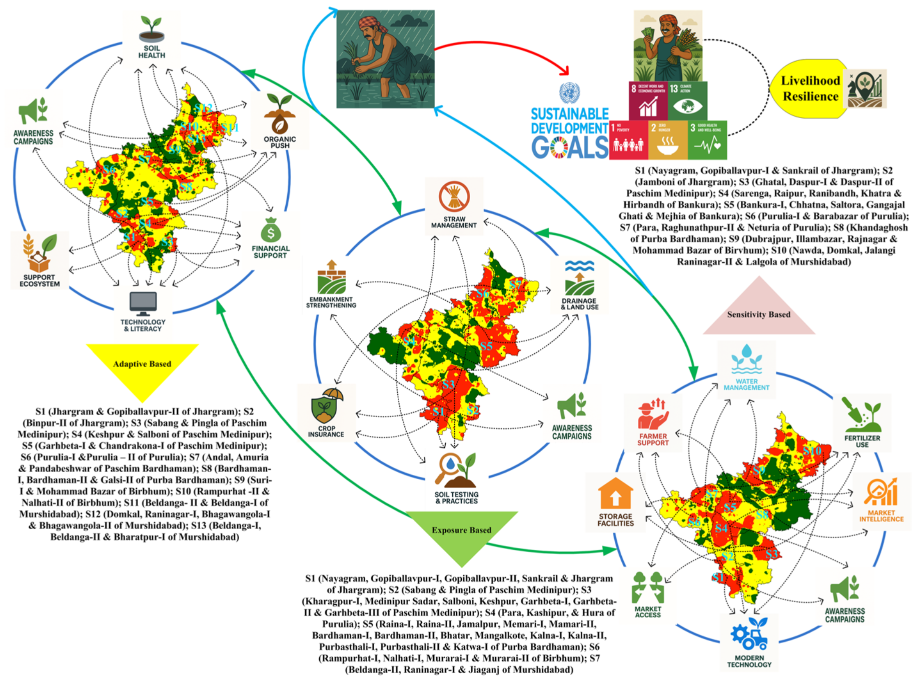


Fig. 6 Category-wise representation (Adaptive, Exposure, and Sensitivity) of site-specific recommendations

7 Limitation of the study

The study's limitations include its narrow focus on rice farmers in eight districts of West Bengal, which may limit generalizability to other crops and regions. Data collection challenges, assumptions based on IPCC conditions, and potential oversights in socio-economic factors could affect the accuracy and completeness of the vulnerability analysis. Additionally, the modeling approach may simplify complex interactions within the agricultural system, and the study's snapshot approach may not capture temporal changes or fine-scale variations in vulnerability factors. Lack of stakeholder engagement may impact the results of the study. Somehow, very remote areas' data are not captured by surveyors due to a lack of connectivity.

8 Recommendations

The research is also focused on category-wise, concise recommendations for policy and management plans to address the livelihood vulnerability of farmers, which is pointed out below and visually represent in a Fig. 6.

8.1 Adaptive capacity based

i. *Awareness Campaigns*: A major constraint observed across multiple blocks such as Jhargram, Gopiballavpur-II, Binpur-II, Keshpur, Salboni, Purulia-I, Purulia-II, Suri-I, Mohammad Bazar, Rampurhat-II, Nalhati-II, Beldanga-I, Beldanga-II, and Bharatpur-I is the lack of awareness regarding rice-fallow pulse (RFP) cultivation practices and the potential of agri-entrepreneurship. Farmers in these areas often rely on traditional knowledge with limited access to recent advancements. To address this, targeted awareness campaigns must be introduced in collaboration with agricultural extension agencies. These campaigns should focus on enhancing knowledge about RFP practices, seasonal planning, and the socioeconomic benefits of diversified farming. Simultaneously, they should work toward re-establishing pride in farming and promoting it as a viable enterprise, especially among youth.

ii. *Financial Support*: Blocks like Sabang, Pingla, Jhargram, Gopiballavpur-II, Garhbeta-I, Chandrakona-I, Bardhaman-I, Bardhaman-II, Galsi-II, Rampurhat-II, Nalhati-II, and Bharatpur-I report difficulties in accessing affordable credit, which hampers timely input purchase, mechanization, and risk-taking ability. These regions often experience dependency on informal credit and lack linkages to institutional finance. Therefore, providing financial support through incentives, interest subvention on agricultural loans, and flexible repayment schemes becomes essential. Policies should also include insurance-linked credit models and facilitate direct benefit transfers (DBT) for small and marginal farmers in these blocks to reduce financial stress and encourage investments in RFP cropping.

iii. *Technology & Literacy*: Low levels of digital literacy and poor access to agro-technology are evident in Jhargram, Gopiballavpur-II, Sabang, Pingla, Purulia-I, Purulia-II, Beldanga-I, Beldanga-II, Domkal, Beldanga-I, Beldanga-II & Bharatpur-I. These areas often lack access to real-time information on weather, markets, or best practices, and farmers are generally unaware of how to operate or utilize tech-enabled services. Policy actions must focus on establishing agro-tech hubs equipped with advisory desks, demonstration farms, and ICT kiosks. In parallel, digital literacy programs and capacity-building workshops must be launched, targeting youth and women, to bridge the rural digital divide and foster tech-led decision-making in agriculture.

iv. *Soil Health*: Soil degradation and unbalanced fertilizer use are prominent issues in blocks such as Purulia-I, Purulia -II, Keshpur, Salboni, Bardhaman-I, Bardhaman-II, Galsi-II, Beldanga-I, Beldanga-II, Domkal, Raninagar-I, Bhagawangola-I, and Bhagawangola-II. These problems lead to stagnating yields and declining resilience of farming systems. Policy interventions should focus on implementing regular soil testing programs, distribution of soil health cards, and training modules on integrated nutrient management. Incentives for adopting organic amendments and green manuring must be included. A decentralized network of mobile soil testing vans can support accessibility in remote blocks, ensuring localized solutions for soil fertility restoration.

v. *Organic Push*: Several blocks including Keshpur, Salboni, Garhbeta-I, Chandrakona-I, Andal, Amuria, Pandabeshwar, Domkal, Beldanga- II, Beldanga-I and Raninagar-Ilimited exposure to organic farming despite favorable potential. High input cost and market uncertainties discourage adoption. To strengthen organic transition, policies must support the development of local bio-input production units, provide subsidies on certified organic inputs, and enable farmers to form organic producer groups. These groups can collectively access certification services and market platforms, reducing barriers to entry. Awareness programs should also include composting techniques and pest management using traditional knowledge.

vi. *Support Ecosystem*: Regions like Jhargram, Gopiballavpur-II, Purulia-I, Purulia-II, Andal, Amuria, Pandabeshwar, Suri-I, Mohammad Bazar, Beldanga-I, Beldanga-II, and Bharatpur-I lack structured support systems like farmer producer organizations (FPOs), agri-advisory units, and input/service cooperatives. This limits their ability to negotiate better prices, access bulk inputs, or receive timely support. Policy should focus on establishing block-level support ecosystems involving local youth and trained agri-entrepreneurs. These ecosystems can provide handholding support on crop planning, procurement, marketing, and risk management. Additionally, convergence with existing schemes like PM-KISAN, ATMA, and KVKs will ensure sustainability and integration.

8.2 Exposure based

i. *Drainage & Land Use*: Several blocks shown in the exposure-based map—such as Ghatal, Daspur-I, Daspur-II, Sabang, Pingla, Kharagpur-I, Raina-I, Raina-II, Jamalpur, Memari-I, Mamari-II, Bardhaman-I, Bardhaman-II, Bhatar and Mangalkotefrequently face waterlogging and poor drainage conditions that delay Rabi pulse sowing. To mitigate this, localized drainage planning must be undertaken, including construction of field channels, land levelling, and community-managed drain lines. In addition, sustainable land use practices should be promoted in Purulia blocks like Para, Kashipur, and Hura, emphasizing flood-prone area zoning and water-efficient cropping systems.
ii. *Embankment Strengthening*: The embankment-vulnerable blocks like Sabang, Pingla, Jamalpur, Memari-I, Memari-II, Bardhaman-I, Bardhaman-II, Bhatar, Mangalkote, Kalna-I, Kalna-II, Purbasthali-I, Purbasthali-II, and Katwa-Ilocated in Purba Bardhaman—require urgent reinforcement due to their exposure to rivers and canals. Strengthening these embankments, involving local panchayats in regular monitoring, and introducing flood early warning systems can reduce crop damage and ensure resilience. Policies should emphasize maintenance budgets, embankment design upgrades, and community disaster preparedness programs.
iii. *Crop Insurance*: Many blocks asNayagram, Gopiballavpur-I, Gopiballavpur-II, Sankrail, Jhargram, Rampurhat-I, Nalhati-I, Murarai-I and Murarai-II suffer frequent crop losses due to unpredictable weather. Inclusion under the Pradhan Mantri Fasal Bima Yojana (PMFBY) and improved awareness on claim filing processes are essential. Block-level insurance camps, premium subsidies for pulses, and digital claim tracking must be integrated into state schemes.
iv. *Straw Management*: Post-harvest straw burning remains prevalent in blocks such as Kharagpur-I, Medinipur Sadar, Salboni, Keshpur, Garhbeta-I, Garhbeta-II, Garhbeta, Para, Kashipur, Hura, Beldanga-II, Raninagar-I and Jiaganj leading to loss of soil nutrients and environmental degradation. To address this, alternative uses of paddy residue—like composting, mushroom cultivation, and bio-energyshould be encouraged. Equipment such as Happy Seeders and Super Straw Management Systems (Super SMS) should be subsidized through Custom Hiring Centres (CHCs), with support for setting up local residue recycling hubs and training entrepreneurs in biomass aggregation.
v *Soil Testing & Practices*: Nutrient deficiencies and unbalanced fertilizer application are limiting pulse productivity in blocks like Jhargram, Garhbeta-III, Salboni, Kharagpur-I, Medinipur Sadar, Salboni, Keshpur, Garhbeta-I, Garhbeta-II, Garhbeta-III, Para, Kashipur, and Hura. Comprehensive soil testing campaigns using mobile soil labs and kiosks should be implemented to guide crop nutrient management. Farmers should be issued Soil Health Cards and provided with micronutrient kits. Training through Krishi Vigyan Kendras (KVKs) and demo plots will help build awareness of sustainable nutrient practices.

vi. *Awareness Campaigns*: Effective outreach is necessary across vulnerable blocks like Nayagram, Gopiballavpur-I, Gopiballavpur-II, Sankrail, Jhargram, Para, Kashipur, and Hura. Campaigns should inform farmers on climate-resilient pulse practices, insurance schemes, water management, and mechanization. This can be done through extension officers, community radio, local wall paintings, and farmer group meeting.

8.3 Sensitivity based

i. *Modern Technology*: In blocks such as Nayagram, Gopiballavpur-I, Sankrail, Sarenga, Raipur, Ranibandh, Khatra, Hirbandh, Nawda, Domkal, Jalangi Raninagar-II and Lalgolapulse production is hindered by high labor costs and delayed operations due to workforce shortages. Farmers here lack access to efficient sowing, harvesting, and processing tools. Promoting the use of modern agricultural machines and establishing Custom Hiring Centres at the block level will reduce manual costs and enhance pulse productivity. These initiatives should include training programs and group-based equipment sharing models.
ii. *Fertilizer Use*: Overuse of chemical fertilizers has led to soil fatigue and micronutrient deficiency, particularly in Ghatal, Daspur-I, Daspur-II, Sarenga, Raipur, Ranibandh, Khatra, Hirbandh, Bankura-I, Chhatna, Saltora, Gangajal Ghati, Mejhia, Para, Raghunathpur-IIand Neturia. Farmers continue to rely heavily on subsidized urea, neglecting soil-specific nutrient needs. A corrective approach involves implementing soil health card schemes, promoting organic and bio-fertilizers, and supporting Integrated Nutrient Management programs through awareness and financial incentives.
iii. *Storage Facilities*: Lack of storage infrastructure in Jamboni, Sarenga, Raipur, Ranibandh, Khatra and Hirbandh forces farmers to distress-sell pulses at low prices. Policies must enable the construction of community grain banks, mini-silos, and rural godowns. These should be managed by FPOs or SHGs, and include linkages to MSP procurement or local aggregators. Post-harvest loss reduction will directly improve farm income.
iv. *Farmer Support*: In areas like Jamboni, Bankura-I, Chhatna, Saltora, Gangajal Ghati, Mejhia, Purulia-I and Barabazar farmers face climate vulnerability, repeated crop failure, and low profitability, resulting in psychological and financial stress. Government-backed farmer support programs should include crop insurance, credit access, counseling, and extension services. Support should also promote entrepreneurship, diversification, and value addition for income stabilization.
v. *Market Intelligence*: Blocks such as Sarenga, Raipur, Ranibandh, Khatra, Hirbandh, Khandaghosh, Dubrajpur, Illambazar, Rajnagar and Mohammad Bazar suffer from limited market access, price awareness, and over-dependence on local traders. Setting up a digital market intelligence platform, SMS-based alerts for price updates, and buyer-seller meetups will boost transparency. Integrating these blocks into e-NAM or state mandi systems will expand their selling options.
vi. *Water Management*: Water scarcity and irrigation inefficiency are critical in Nayagram, Gopiballavpur-I, Sankrail, Bankura-I, Chhatna, Saltora, Gangajal Ghati, Mejhia, Para, Raghunathpur-II and Neturia which hampers optimal pulse growth. Policies must encourage rainwater harvesting (RWHS), farm ponds, and adoption of drip/sprinkler

irrigation systems. Block-level irrigation audits and farmer incentives for water-saving technologies are essential for climate resilience.

vii. *Market Access*: Transportation bottlenecks in Ghatal, Daspur-I, Daspur-II, Para, Raghunathpur-II and Neturia restrict farmers from reaching larger markets or procurement centers. Upgrading rural road connectivity under schemes like PMGSY, introducing community-run transport vans, and establishing local aggregation hubs will improve market access and reduce costs.

9 Conclusions

This study provides a comprehensive assessment of livelihood vulnerability among rice farmers across eight agro-ecologically distinct districts of West Bengal using the LVI-IPCC framework and the EDAS multi-criteria decision analysis model. By integrating field-derived socio-economic, climatic, and environmental indicators, the study identifies significant spatial disparities in vulnerability, shaped by differential exposure, sensitivity, and adaptive capacity. Districts such as Jhargram, Birbhum, and Murshidabad exhibit the highest levels of vulnerability (27.86–48.16%) due to low adaptive capacity, erratic rainfall, and groundwater contamination. In contrast, Purba Bardhaman and Paschim Bardhaman demonstrate relatively lower vulnerability (7.43% and 15.32%) owing to better irrigation access and socio-economic infrastructure. These spatial differences highlight the need for district-specific adaptation strategies.

The findings reveal that rice farmers are increasingly adopting unsustainable coping mechanisms, including elevated input usage and labor investment, which are proving insufficient in the face of escalating climate stress. Key exposure factors—such as temperature variability, extreme rainfall, and water stress-particularly affect farmers in the western plateau zone. There is an urgent need for targeted interventions, including livelihood diversification, climate-resilient crop varieties, water-saving technologies, and institutional support for localized adaptation planning. Methodologically, the integration of EDAS modeling with field-based vulnerability indicators provides a scalable and adaptable framework for other climate-stressed regions. The study's policy relevance is reinforced through alignment with UN Sustainable Development Goals (SDGs 1–3, 8, and 13).

However, certain limitations must be acknowledged. The study's geographic focus on eight rice-producing districts may limit broader applicability. Data collection constraints, limited stakeholder engagement, and the exclusion of some remote locations due to connectivity issues are recognized weaknesses. The study's cross-sectional design also restricts temporal analysis, potentially overlooking long-term feedback mechanisms. Future research should incorporate longitudinal datasets, real-time climate monitoring, and advanced techniques such as machine learning or deep learning to enhance predictive power and spatial precision. Participatory approaches and integration with open-access GIS platforms can further strengthen the policy utility of such assessments. In conclusion, the study highlights both the urgency and opportunity to secure rice farmer livelihoods through district-tailored, data-informed resilience strategies, with potential for broader application in climate-vulnerable agricultural systems.

Supplementary Information

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Supplementary Material 1

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Author contributions

Conceptualization, S.S., S.M., A.G.; methodology, S.S., S.M., A.G.; software, S.M., S.S., A.G; validation, S.S., S.M., A.G; formal analysis, S.M., S.S., A.G; investigation, S.S., S.M., A.G; resources, S.S., S.M., A.G.; data creation, S.S., S.M., writing—original draft preparation, S.S., S.M.,. A.G.; writing—review and editing, S.S., S.M., A.G., visualization, S.S.; supervision and revision, A.G., S.S; project administration, A.G.; All authors have read and agreed to the published version of the manuscript.

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Data availability

The data that support the findings of this study are not publicly available due to confidentiality agreements with the participants. Interested readers may contact the corresponding author for further information and access to anonymized data, if appropriate.

Declarations

Ethics approval and consent to participate

The protocol for this study was approved by the Ethics Committee of the International Center for Agricultural Research in the Dry Areas (ICARDA), in accordance with ICARDA's ethical guidelines and relevant national regulations. Prior to the design and implementation of the study, all necessary permissions were obtained from the respective provincial authorities.

Consent for publication

Consent to the publication of this research, confirming all necessary approvals and participant consents were obtained.

Informed consent

Before enrolling participants, informed consent was obtained from all participants involved in the study. The participants provided their verbal consent after being informed about the purpose, nature, and intended outcomes of the research. Participation was entirely voluntary, and strict confidentiality and anonymity were maintained throughout the data collection process. For participants under the age of 18, consent was obtained from a parent or legal guardian.

Competing interests

The authors declare no competing interests.

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