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Determinants of farm household resilience and its impact on climate-smart agriculture performance: Insights from coastal and non-coastal ecosystems in Odisha, India

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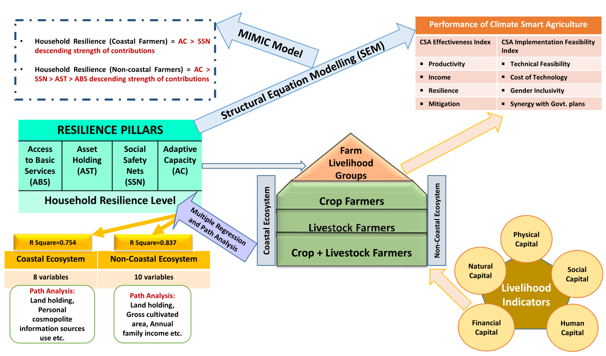
HIGHLIGHTS

- Understanding resilience determinants is crucial for promoting climate-smart and sustainable agriculture
- Key factors influencing farm household resilience identified in coastal and non-coastal ecosystems of Odisha, India.
- Crop-livestock farmers exhibit the highest resilience, followed by crop and livestock farmers.
- Using RIMA framework and SEM, interconnections between resilience determinants and CSA performance is revealed.
- Targeted interventions are required to enhance climate resilience and promote climate-smart agricultural practices.

GRAPHICAL ABSTRACT



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ABSTRACT

Context: Climate change presents severe challenges to agricultural production systems, particularly for small-holder farmers in developing nations like India. Strengthening the resilience of farm households is crucial for sustaining agricultural productivity in the face of climatic uncertainties. To enhance the effectiveness and upscaling of Climate Smart Agriculture (CSA) interventions, agricultural systems must be restructured and reformed considering resilience of farm households. Understanding the influencing factors of farm household resilience as well as effect of resilience pillars in improving the CSA performance is essential.
Objective: Present study aims to identify the key determinants of farm household resilience across coastal and non-coastal ecosystems in Odisha, India, a highly climate-vulnerable state. It seeks to analyse the interrelationships between resilience determinants and explore the link between farm household resilience and CSA performance in terms of effectiveness and implementation feasibility as perceived by the farmers.

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Methods: The study investigates the resilience of farm households across coastal and non-coastal ecosystems, focusing on three dominant livelihood groups: crop farming, livestock farming, and combined crop-livestock farming. It employs the Resilience Index Measurement and Analysis (RIMA) framework to assess resilience through four key pillars: Access to basic services (ABS), Assets (AST), Social safety nets (SSN), and Adaptive capacity (AC). A Multiple Indicators Multiple Causes (MIMIC) model is used to examine resilience determinants, while Structural Equation Modeling (SEM) is applied to assess the relationship between household resilience and CSA performance. Additionally, multiple regression and path analysis are conducted to identify resilience drivers in terms of livelihood indicators across coastal and non-coastal ecosystems.

Results and conclusions: Findings indicate that crop-livestock farming households exhibit the highest resilience in both coastal and non-coastal regions, while crop farmers demonstrate higher resilience than livestock farmers. The study uncovers distinct resilience drivers between coastal and non-coastal areas. SEM analysis highlights a differential relationship between resilience and CSA performance, revealing how resilience influences CSA outcomes. It suggests a moderately fit model highlighting AC and SSN pillars contributing to resilience. Multiple regression and path analysis have revealed key livelihood indicators (such as infrastructure, connectivity, community network, landholding, irrigation access, and income) determining the resilience of the farmers. These insights contribute to a deeper understanding of micro-level resilience among farm households and its relationship with CSA performance.

Significance: By identifying key resilience determinants beyond traditional adaptive capacity, this study provides critical policy inputs for fostering climate-resilient agri-food systems. The findings emphasize the need for targeted interventions to strengthen farm household resilience and promote sustainable, climate-smart agricultural practices in vulnerable regions.

1. Introduction

Almost all ecosystems across the globe are now experiencing the concomitant effects of climate change in terms of melting glacier caps, rising global sea level, increasing frequency of extreme weather events such as tropical cyclones, floods, droughts, heatwaves etc., increasing pest infestations, and adverse impacts on human and livestock settlements (IPCC, 2022; IPCC, 2014a, 2014b; UNISDR (United Nations Office for Disaster Risk Reduction), 2004). Climate change and extreme weather events can cause compound, complex and cascading effects on ecosystems in an area. Many researchers have attempted to address the issues of climate change by first understanding the complex level of interactions between humans and their existing ecosystems (Inaotombi and Mahanta, 2018; Diaz et al., 2015; Engle et al., 2014). The pronounced effects of climate change visibly affect the agriculture and agrarian economy of the underdeveloped and developing nations (Azadi et al., 2021; World Bank, 2012). This calls for examining the micro level farm households of these nations and their resilience level for efficient handling of location-specific climate change issues (Das and Ansari, 2021; Jha et al., 2021; Rauken et al., 2015). As climate change will alter the precipitation and temperature patterns over the next few decades, efforts to boost resilience of farm households will be crucial for sustaining food production, farm income, and food security (Randell et al., 2022).

Due to their comparatively greater reliance on agriculture for their livelihoods, developing nations like India are more likely to be negatively impacted by impending climate change (Rama Rao et al., 2019). Climate change poses a greater threat to Indian farmers, particularly those who are marginal and smallholder (own less than 2 ha of land) (Cruz et al., 2007). Climate change has pushed farmers beyond their coping capacities, necessitating long-term (mitigation) and short-term (adaptation) interventions to ensure resilient, sustainable, and secure farming systems (Jarvis et al., 2011). Climate Smart Agriculture (CSA) is advocated as a potential solution (FAO, 2013). There are three pillars of CSA- (i) increasing agricultural productivity to support sustainable livelihoods, (ii) adaptation and capacity building to bring out resilient agricultural systems, and (iii) mitigation by reducing the GHGs emissions to a safe level. With the agricultural sector being the largest consumer of water resources (Misra, 2013; Amarasinghe et al., 2007), climate change events such as droughts and heat waves severely affect the availability of water for irrigation thereby the agricultural production. Coastal ecosystems are typically sensitive to adverse climatic impacts from tropical cyclones, submergence, and coastal flooding (Schaller et al., 2016). In contrast to coastal ecosystems, weather extremes are different for non-coastal ecosystems, where, drought and heatwave are major concern. Thus, studying the resiliency of inhabitants in these contrasting ecosystems, each of which is uniquely exposed to climatic vagaries, is crucial.

There has been an increasing trend of population pressure and assets exposed to coastal risks since the beginning of the 21st century (IPCC, 2014b). Additionally, in many related studies, there is an urgent need to understand the aided anthropogenic factors that contribute directly or indirectly to climate change events in general and drought and heat waves in particular affecting non-coastal ecosystems (Buzási et al., 2021; Misra, 2013; Zou et al., 2012; Bryant, 2005). The fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC) suggested that a major portion of the world will face adverse effects from climate change, such as drought and heat waves (IPCC, 2014a, 2014b; Tsubo et al., 2009). And, livelihood of farm households inhabiting in these contrasting ecosystems are threatened differentially due to climatic calamities (Das et al., 2022a, 2022b; Ayanlade et al., 2017; Sheikh and Akter, 2017; Alam et al., 2016). Thereby leaving behind questions to address as "how resilient the farm families are to extreme climatic events in coastal and non-coastal regions?", "which farm livelihood groups show a better resilience?", "is the resilience related with the performance of CSA interventions?" and "what are the livelihood attributes that influence the farm household resilience?"

Farm households tend to withstand and/or escape the adverse impacts of climate change using suitable adaptation mechanisms (Abbass et al., 2022; Fankhauser, 2017). However, most studies indicate only the vulnerability of such households and drivers of vulnerability that impact their choice of adaptation mechanisms (Fadairo et al., 2023; Kling et al., 2020; Owusu and Nursey-Bray, 2019). Estimating the adaptive capacity of households in climatically vulnerable regions has been an emerging trend since the emergence of concepts relating to vulnerability, resiliency, and climate change (Cohn et al., 2017; David et al., 2016; Adger et al., 2009). Additionally, addressing aspects like vulnerability or resiliency studies in silos has left many dimensions unaddressed, typically the structural organization of a resilient household and its resilience capacity, which is a function of its pillars (RMTWG (Resilience Measurement Technical Working Group), 2014). Further, with a compound risk to drought and heatwaves and several other climatic calamities, a single adaptation practice will not suffice. This leads to an urge to adopt CSA that addresses composite pillars of the productivity, adaptation and mitigation of a farm household (Das et al., 2022a, 2022b; Aryal et al., 2018). Thus, here is a research gap to address the resiliency of farm households and establishing a relational model that drives the effectiveness and implementation feasibility of CSA practices at a given level of resiliency.

The household resiliency can be defined as the ability to prevent disasters and crises as well as to anticipate, absorb, accommodate, or recover from them in a timely, efficient, and sustainable manner (FAO, 2013). The definition of resiliency as put forth by the RMTWG (Resilience Measurement Technical Working Group) (2014) is “the capacity that ensures adverse stressors and shocks do not have long-lasting adverse development consequences”. And improving household resilience is increasingly a significant social protection programme in Africa (Abay et al., 2022) and most developing countries, often complemented with various income-generating and asset-building initiatives. According to Folke et al. (2010), there are two types of resilience: general resilience, which is the ability to handle any issue, including new ones, and specific resilience, which is the ability to deal with a specific crisis, such as climate change. Understanding the resilience levels of various strata of farmers as a preventive measure and a component of disaster preparedness is crucial (Chanie et al., 2018). The farm and farmer attributes explain the resilience of a farming system; therefore, identification of the key attributes of farm(er) to explain farmers’ resilience has been emphasized (Prat-Benhamou et al., 2024). The resilience studies have considered the three resilience capacities (robustness, adaptability, and transformability) of the farm (Spiegel et al., 2021; Prat-Benhamou et al., 2024). However, resilient capacity of farm households are not adequately addressed; no studies could be stressed to relating the resilient capacity of farm households with the adoption of climate smart agriculture practices that is reported as low in India despite of initiatives like National Innovations on Climate Resilient Agriculture (NICRA) by Indian Council of Agricultural Research (ICAR) (Aryal et al., 2018).

In this backdrop, the present study was undertaken in the eastern Indian state of Odisha with the specific objectives i) to study the level of farm household resiliency towards climate change and its influencing factors, and ii) to fit a relational model between the farm household resiliency and CSA performance in the contrasting coastal and non-coastal ecosystems. This paper presents the resilience of households in the form of resilience capacity and a resilience structure matrix, and their functional relationship with the performance of CSA. The livelihood indicators influencing the resilience level of farm households are also delineated for future policy advocacy to improving the farm household resilience and the adoption CSA interventions. This methodological approach enables an in-depth understanding of resilience of farming households in climatically vulnerable regions, helping to inform targeted policy measures and the practical implementation of CSA interventions in small holders agricultural systems worldwide. The outcomes are intended to guide strategic investments, uplift specific resilience dimensions, and enhance CSA performance across coastal and non-coastal ecosystems in other developing countries.

2. Methodology

The resilience of farm households is expected to vary across ecosystems and farm livelihood options. Therefore, the present study was conducted in a eastern Indian state of Odisha with contrasting ecosystems and extreme climate vulnerability. The state is 3rd worst hit states to climate change (SOE, 2021). And due to the strategic geographic location of the state with long coastline and non-coastal land locked ecosystems, the state was suitable for the study which other two top worst hit states (Jharkhand and Mizoram) lack. The state of Odisha is geographically located on the coast of the Bay of Bengal, which features an extensive network of rivers that are highly exposed to climatic vagaries, such as cyclones and floods. The change in mean temperature along with altered rainfall patterns causing drought is no exception for this state (GoO, 2016). The state is hit worst by tropical cyclones very frequently (Bahinipati, 2014), and floods are the next serious disasters causing the state to run to restore the status quo after a disaster (GoO, 2010; GoO, 2016). In contrast, approximately 50 % of the state’s area is under the constant threat of drought and water scarcity (Deccan Herald, 2019). Odisha is a state with one of the lowest per capita incomes in India. Predominantly, the rural livelihood of Odisha is agriculture, followed by agri-allied occupations, with most of the farm households falling into marginal and small categories.

2.1. Sampling framework

The study employed a mixed sampling technique by administering both purposive sampling to select the study area (districts) and stratified random sampling proportionate to the population size to select the respondents for field survey. The study area was chosen purposively in the two districts where the Indian Council of Agricultural Research (ICAR) has implemented its flagship programme, National Innovations in Climate Resilient Agriculture (NICRA); accordingly, one coastal (Kendrapara) and non-coastal district (Dhenkanal) were selected. The coastal and non-coastal areas of these districts, where NICRA was implemented, have three dominant farm livelihood groups, as inferred during the pilot surveys conducted in the study areas, viz. farmers practicing crop farming, livestock farming, and crop+livestock farming. The study operationalized crop farmers as the farmers deriving more than 51 % of their livelihood solely from crop farming; livestock farmers as the farmers deriving more than 51 % of their livelihood solely from livestock farming and crop + livestock farmers as the farmers deriving their livelihood from both the enterprises but none exceeded 50 % of the total livelihood received. These three dominant farm livelihood groups formed the three strata, where from, a total sample of 200 farmers, 100 farmers from each district, was selected, ensuring representation from each of the three major livelihood groups proportionate to their population size within the coastal and non-coastal areas of two respective districts. Thus, a sample of 55 crop farmers, 25 livestock farmers, and 20 crop+livestock farmers in coastal district of Kendrapara, and 55 crop farmers, 25 livestock farmers, and 20 crop+livestock farmers in coastal district of Kendrapara, and 60 crop famers, 20 livestock farmers, and 20 crop+livestock farmers in non-coastal district of Dhenkanal were the respondents for the field survey conducted during 2021–22 under present study.

2.2. Resilience measures

Resilience as a concept addresses the fundamental unpredictability due to climate change. It allows informing ground realities based on vulnerabilities, shocks, stressors, uncertainties coupled with adaptation and transformation (Shaw and Maythorne, 2013). Resiliency plays a crucial role in risk-prone environments for policy makers. Understanding how households cope with stressors and shocks is a promising concept. Further, resilience is unique with respect to time and area, specific to livelihood and shocks/stressors (Béné, 2013); thus, there is a need to modify the indicators and dimensions encompassing resilience. Climate change, when combined with social dynamics and economic conditions, increases the frequency and intensity of risk exposure among vulnerable people. Thus, Resilience Index Measurement and Analysis (RIMA II) of the FAO (2016), was used to measure the resilience of the farm households. Several studies reflect the use of this framework as a robust method of reporting household resilience (Okyere et al., 2024; Ali et al., 2023). Further, insights into characteristics of household under four resilience pillars can reveal the implications for policy advocacy and sustainable livelihood outcomes through CSA (Asfaw and Branca, 2018; Woldemichael et al., 2023; Do et al., 2025).

RIMA II framework employs latent variable models to estimate the Resilience Capacity Index (RCI) and resilience structure matrix (RSM). The resilience pillars estimated through the RIMA II include access to basic services (ABS), household assets (AST), social safety networks (SSN), and adaptive capacity (AC). These four constructs (latent variables) were employed to measure the four pillars of farm household resilience and were included in the structural model as exogenous variables and measured through several observed indicators.

The ABS reflects the ability of a household to meet basic needs through the extent of accessibility and effective use of basic services, e.g., access to schools, health facilities, infrastructures, and markets. AST comprises both productive and nonproductive assets such as land, livestock, and durables. The SSN pillar measures the ability of households to access timely and reliable assistance provided by national and international agencies, charities, and NGOs, as well as help from relatives and friends. AC is the ability of a household to adapt to a new situation and develop new strategies of livelihood. Other tangible assets, such as houses, vehicles, and household amenities, reflect the living standards and wealth of a household.

The RCIs were estimated following factor analysis: from observed variables to the four pillars, and thereafter from the pillars to the RCIs. The ultimate output of the RIMA has given us an idea of who were the neediest during the hour of climate crisis, where the investment focus should be readjusted for better geographical accessibility, which dimensions of resilience need uplift and to what extent the target populations have become resilient. The working unit of the RIMA is the "household" because within a household, the most important decisions to manage uncertainties are made, and this unit represents the ultimate beneficiary of any shock due to climatic vagaries and benefits from the positive effects of any policy advocacy. Therefore, the RIMA provides information on "household resilience capacity." It is a vital tool for policy analysis to guide funding and policy decisions, as it allows targeting and ranking households from most to least resilient.

The RIMA II methodology serves as a predictive measure of a household's inherent capacity to recover from potential future shocks (Ciani and Romano, 2014; FAO, 2020; Woldemichael et al., 2023) making it a suitable methodology in the present context. After working out the RSM and RCI of the farm households, the present study has also attempted to model the climatically vulnerable agri-ecosystem's outcome- CSA performance with the resilience profile of farm households.

2.3. CSA performance

The outcome of climatically vulnerable agricultural system depends on the performance of CSA interventions, which was assessed in terms of effectiveness and implementation feasibility (Das et al., 2022a, 2022b). Present study considered three domains of CSA, viz., productivity, resilience and mitigation as defined by FAO (2013) as well as income as fourth domain following the recent researchers (Khatri-Chhetri et al., 2017; Wassmann et al., 2019; Singh et al., 2021) to measure the effectiveness of CSA interventions. The CSA interventions promoted under NICRA were considered for evaluation (refer Das et al., 2022a, 2022b for the further detail). Farmers were initially asked to assign weights to the four CSA effectiveness indicators on a scale of 1–4 as per their mutual priority followed by their response on the CSA interventions on 10-point continuum (0 being no impact and each unit indicating 10 % improvement). According to the weights derived through rank-sum method, coastal district farmers have prioritized income (38 %), productivity (27 %), resilience (25 %), and mitigation (10 %) when evaluating the effectiveness of CSA interventions, while non-coastal district farmers prioritise income (37.7 %), productivity (28.1 %), resilience (24.2 %), and mitigation (10 %), respectively. The CSA effectiveness index (CSAEI) was calculated by multiplying the mean response score of each of the four domains with their respective weights and summing-up. Similarly, the implementation feasibility of CSA practices was also indexed (CSAIF) based on technical feasibility, cost of technology, gender inclusivity and synergy with government plans as perceived by the farmers (Das et al., 2022a, 2022b; Khatri-Chhetri et al., 2019). The weights of the indicators were derived based on principal component analysis and accordingly, coastal farmers have given more emphasis on technical feasibility (0.270), followed by synergy with government programmes (26 %), technology cost (25 %), and gender inclusivity (22 %); however, the non-coastal farmers have emphasized on the cost of technology (28.7 %) followed by gender inclusivity (28.3 %), technical feasibility (23 %), and synergy with government programmes (20 %). Farmers responses were obtained on a 5-point continuum Likert scale (0 = not relevant, 1 = very low importance, 2 = low importance, 3 = medium importance, 4 = high importance and 5 = very high importance), which was multiplied by the respective weight and summed-up to derive the index value.

2.4. Relationship between resilience and CSA performance

The mathematical representation of household resilience from the equations by Andreas and Friedrich, 2008 can be stated as follows:

$$y = \alpha\eta + \epsilon \tag{1}$$

$$\eta = \gamma' x + \zeta \tag{2}$$

where,

η = latent variable (household resiliency).
γ = coefficient of latent variable η.
$y_1, y_2, \ldots, y_n$ = indicators of the latent variable.
$x_1, x_2, \ldots, x_n$ = causes of latent variable.

Eq. (1) states that y values are congeneric measures of η, meaning that they all measure the same construct. Here the construct under study is household resiliency and all the indicators intend to measure household resiliency.

To test the hypothesized relationship between the determinants and effects of resilience, the following (baseline) multiple indicators multiple causes (MIMIC) model of resilience (η) was implemented.

The basic causes of the structural model used in the modeling process of the MIMIC model are ABS, AST, SSN and AC:

$$[\eta] = [\beta_1, \beta_2] \times \begin{bmatrix} ABS \\ AST \\ SSN \\ AC \end{bmatrix} + [\varepsilon_1] \tag{3}$$

Here, we have assumed the reflective model that hypothesized that resilience (η) is influenced by the pillars (x_i). The formative indicators are assumed to be correlated and measured.

The MIMIC model permits simultaneous estimation of the measurement model and the incorporation of causal variables in the structural model for the latent variable resiliency, which is linearly determined (apart from random errors, ε_1) by formative indicators or pillars.

The household resilience capacity relates with the performance of CSA interventions in terms of their effectiveness and implementing feasibility. To construct and assess this relationship, a PLS-based structural equation modeling procedure was followed given the method's suitability for assessing the model with minimal assumptions compared with the CB-based model. The analysis was conducted via SMART PLS.

2.5. Livelihood indicators determining resiliency

A livelihood comprises the capabilities, assets (including both material and social resources) and activities required for a means of living. A livelihood is sustainable when it can cope with and recover from stresses and shocks, maintain or enhance its capabilities and assets, while not undermining the natural resource base (Chambers and Conway, 1992). To measure the level of livelihoods of farm households, 33 indicators were selected under the physical, social, financial, human, and natural capitals based on the Sustainable Livelihoods Framework of DFID (1999). These indicators were measured (Das et al., 2024) and considered as the independent variables influencing the farm household resilience to climate change events (Table 1). Multiple regression (backward elimination method) and path analysis were employed to

Table 1
List of variables (livelihood indicators) and their measurement as per the DFID framework.

Variable Name	Measurement	Source followed the DFID framework (DFID, 1999)
Conveyance	Type of Conveyance used along with no. of units owned by the farmer	**Physical Assets** (Samsudin and Kamarudin, 2013; Scoones, 1998; Ahmed et al., 2008)
Road connectivity to and from the village	Type of road, where scoring pattern followed as metalled/ tarred road = 4, concrete road = 3, Bricks road = 2, unmetalled road = 1. and condition of road measured on a scale of 1–5 where 5 means very good and 1 means very poor	
Water sources	Type of source for domestic purpose and farm irrigation purpose along with units available was reported	
Communication devices	Units of communication devices available with the farmer was reported	
House type	For humans (Concrete/Semi-thatched/thatched) and for livestock (Concrete/Semi-thatched/thatched) was reported	
Electricity connection	For domestic use and farm use was reported	
Farm machinery and implements	Various types of Farm machinery and implements such as Tractor, power tillers, cultivators, threshers, sprayers etc. along with units available was reported	
Cooking facility	Means of cooking was reported	
Sanitation facility	Available inside the house or outside the house was reported	
Social participation	Social participation as a member/non-member/ participant/office bearer in different social organizations like Farmer Producer Organizations, Cooperatives, Panchayats etc. was reported	**Social Assets** (Aniah et al., 2016; Stirrat, 2004; Mukherjee et al., 2002)
Social cohesiveness	Degree of Social Cohesiveness in different social events was measured on a scale of 1–5 where 1 = very low and 5 = −very high	
Participation in community initiatives	Involvement in no. of Community initiatives was reported	
Accessibility to common facilities	Measured based on awareness (Aware = 1/ Unaware = 0), Accessibility (Yes/No), Distance from house (in km) and Quality of service (very good = 5 and very poor = 1) to various common facilities like Primary health centre, school, college, bank etc.	
Social recognition	Perceived household Status in the society	
Credit behavior	Measured in terms of Access to credit (Easy = 3/ Moderately Difficult = 2 /Difficult = 1) and amount taken as credit from different sources of credit such as moneylenders, friends, relatives etc.	**Financial Assets** (Siyoum et al., 2012; Li et al., 2014)
Annual family income	Amount in Rupees was reported	
Economic status	Perceived as Above Poverty line (>Rs. 27,000/per annum) or Below Poverty Line (<Rs. 27,000/per annum)	
Sources of income	Number of income sources with income in Rupees was reported	
Insurance facilities	Awareness about the insurance facility along with the detail if availed or not was reported	
Annual family expenditure	Amount in Rupees was reported	
Household savings	Amount in Rupees was reported	
Farm size	Land holding in acres/ha was reported	**Natural Assets** (Aniah et al., 2016; Scoones, 1998; Kollmair and Gamper, 2002; Li et al., 2020)
Size of water body	Size in hectare and Number of water body owned by the farmer was reported	
Livestock holding	Units of different types of livestock owned by the farmers was reported	
Gross Cropped Area (GCA)	Amount of land under cultivation in acres/ha in kharif season, in Rabi season and in summer season	
Gross Irrigated Area (GIA)	Amount of land under irrigation in acres/ha in kharif season, in Rabi season and in summer season	
Mass media use	Measured on a scale of very often/daily = 4 to never = 0	**Human Assets** (Rakodi, 2002; Haobijam and Ghosh, 2023)
Information availability	Availability of certain type of information such as Information related to weather, agricultural practice, livestock management etc. measured on a scale of available always = 4 to never available = 0	
Education level	Number of years of education completed indicative of certain level of education	
Personal cosmopolite information sources use	Measured on a scale of very often/daily = 4 to never = 0	
Personal localite information sources use	Measured on a scale of very often/daily = 4 to never = 0	
Extent of suffering/ Family health status	Frequency of suffering along with number of members suffering was reported	
Participation in training and extension activities	Number of times participation in a certain extension/training activity was reported	

determine the total effect, direct effect, indirect effect, and intermediating effect of the significant livelihood indicators on resilience level of farm households both in coastal and non-coastal regions.

3. Results

3.1. Farm household resilience

The resiliency of various livelihood groups is studied based on four pillars, namely, access to basic services (ABS), farm household assets

(AST), social safety nets (SSN) and adaptive capacity (AC). The resilience structure matrix (Fig. 1) explains how each pillar relates to resiliency through the observed variables and how much each observed variable is related to the resiliency pillar. RSM is identified here by the weight that each pillar has in determining the resilience capacity, and each variable has in determining the pillar.

The RSMs for the Kendrapara and Dhenkanal districts are presented in Fig. 1. The weights are assigned following factor analysis of the pillars of resiliency, where the factor loading values of the pillars were considered to derive the weights (Table 2). The factors were renamed based on factor loadings under each derived component in the respective pillars. For the Kendrapara district, the pillar ABS has renamed observable variables, namely, Market & Transport Infrastructure, Access to Health Facility and Access to Primary School and Drinking water, because these together had the maximum contribution to this pillar and subsequently to the resiliency of households. Similarly, the AST pillar included renamed variables, namely, Agricultural Asset Holding and Stationary & Livestock Asset Holding; the SSN pillar included variables, namely, Financial Safety Nets and Social Reliability Network; and the AC pillar included new renamed variables, namely Socio-Economic Capacity. Similarly, for the Dhenkanal district, the ABS pillar was renamed as Distance to Market & Infrastructure Management, the AST pillar was renamed as Farm Asset Holding and Livestock Asset Holding, the SSN pillar was renamed as Financial & Social Nets, and the Formal Transfers & Safety Net Programmes and AC pillar were renamed as Educational Level of Household Head and Agro-Economic Capacity. The RSM of both districts encourages corrective policy actions to include these variables so that households can better cope with the consequences of climatic vagaries at ground level.

The RCI of farm households representing three dominant livelihood groups in both coastal and non-coastal districts are presented in Table 3. The RCIs for both districts were calculated using principal component analysis (PCA) via factor analysis and the MIMIC model via the structural equation modeling technique. Interestingly, the resilience of farmers with two sources of income (such as crop+livestock farmers) was greater than that of those with a single source of livelihood. The crop farmers in both districts were more resilient than the livestock farmers in the respective districts were. The overall resilience capacity of coastal region (Kendrapara district) farmers was better than that of non-coastal region (Dhenkanal district) farmers. Interdistrict comparisons revealed significant z statistics for crop farmers, indicating that there was a significant difference in the resilient capacity of crop farmers, while that of livestock and crop+livestock farmers did not significantly vary. Overall, coastal region farmers have significantly greater resilience than non-coastal region farmers.

To test the significant differences among the different livelihood groups based on their RCIs, analysis of variance (ANOVA) was performed in Statistical Package for Social Science, version 26 (SPSS, version 26) (Table 4). The F statistics were found to be significant for both districts among the different livelihood groups. Based on the test of homogeneity of variance (Levene's statistics) and the robust test of equality of means (Welch statistic and Brown Forsythe statistic), Scheffe's test was used in combination with the post hoc test to determine significant differences among various livelihood groups in both districts.

A test of significance revealed that the resiliency of crop farmers was significantly different from that of livestock farmers in the Kendrapara district. The livestock farmers were significantly different from both the

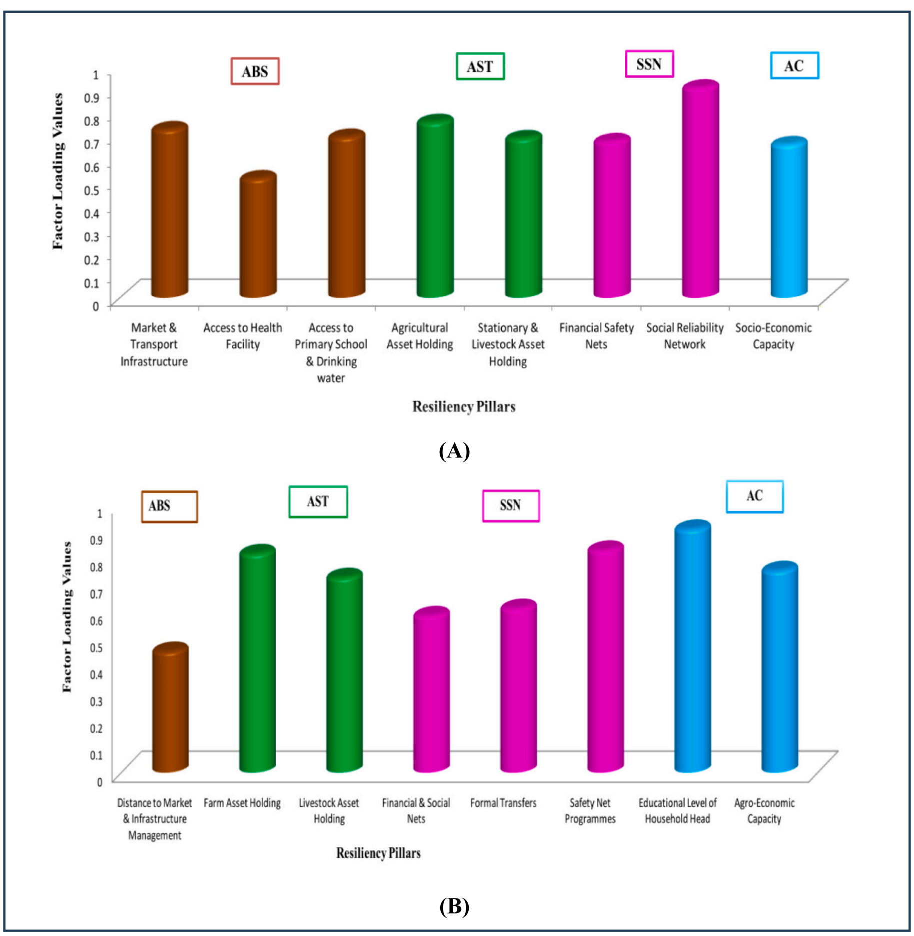


Fig. 1. Resiliency Structure Matrix of (A) coastal (Kendrapara) and (B) non-coastal (Dhenkanal) districts.

Table 2
Conglomeration of variables based on factor loading & renaming of factors pertaining to resilience of farm households in Coastal (Kendrapara) and Non-coastal (Dhenkanal) districts.

Resilience pillars	Variables	Factor loadings		Principal component	Eigen values	Percent of variance	Cumulative %	Factor renaming
		Coastal	Non-coastal					
ABS	Infrastructure (ABSI 1)	0.615	0.137	PC 1- Coastal (ABSI 1, ABSI 2, ABSI 3, ABSI 4)	2.614	37.345	37.345	Market and transport infrastructure
	Distance to the livestock market (ABSI 2)	0.76	0.861	PC 1- Non-Coastal (ABSI 1, ABSI 2, ABSI 3, ABSI 4, ABSI 5, ABSI 6, ABSI 7)	4.010	57.286	57.286	Distance to market and infrastructure management
	Distance to the agricultural/ crop market (ABSI 3)	0.728	0.842	PC 2- Coastal (ABSI 5)	1.248	17.823	55.168	Access to health facility
	Distance to the public means of transport (ABSI 4)	0.813	0.854					
	Distance to health facility (ABSI5)	0.517	0.941	PC 3- Coastal (ABSI 6, ABSI 7)	1.248	16.424	71.592	Access to primary school and d rinking water
	Distance to the water source (ABSI6)	0.762	0.336					
	Distance to the primary school (ABSI7)	0.629	0.902					
AST	Agricultural inputs use (ASTI 1)	0.729	0.836	PC 1- Coastal (AST 1, ASTI 2, ASTI 3)	2.318	38.630	38.630	Agricultural assets holding
	Total cultivated area (ASTI 2)	0.829	0.905	PC 1- Non-Coastal (AST 1, ASTI 2, ASTI 3, ASTI 4)	2.776	46.267	46.267	Farm assets holding
	Total farm produce (ASTI 3)	0.661	0.843					
	Total number of assets (ASTI 4)	0.611	0.677	PC 2- Coastal (ASTI 4, ASTI 5, ASTI 6)	1.578	26.306	64.936	Stationary and livestock assets holding
	Total number of animals (ASTI 5)	0.726	0.792	PC 2- Non-Coastal (ASTI 5, ASTI 6)	1.437	23.955	70.222	Livestock assets holding
	Total number of poultry birds (ASTI 6)	0.732	0.662					
SSN	Loan received (SSNI 1)	−0.442	0.635	PC 1- Coastal (SSNI 1, SSNI 2, SSNI 3, SSNI 4)	1.975	39.503	39.503	Financial safety nets
	Relief food (SSNI 2)	0.818	0.692	PC 1- Non-Coastal (SSN 1, SSNI 3, SSNI 5)	1.528	25.459	25.459	Financial and social nets
	Cash transfer (SSNI 3)	0.773	0.520	PC 2- Coastal (SSNI 5)	1.162	23.245	62.748	Social reliability network
	Livestock transfer (SSNI 4)	0.676	–	PC 2- Non-Coastal (SSNI 2, SSNI 6)	1.312	21.867	47.325	Formal transfers
	Reliable network (SSNI 5)	0.909	0.599					
	Pension schemes (SSNI 6)	–	0.533	PC 3- Non-Coastal (SSNI 7)	1.033	17.218	64.543	Safety net programmes
	Safety net programmes (SSNI 7)	–	0.829					
AC	Years of education of household head (ACI 1)	0.642	0.907	PC 1- Coastal (ACI 1, ACI 2, ACI 3)	1.336	44.541	44.541	Socio-economic capacity
	Number of income sources of the household (ACI 2)	0.602	0.777	PC 1- Non-Coastal (ACI 1)	1.456	48.533	48.533	Educational level of household head
	Number of crops grown by the household (ACI 3)	0.749	0.729	PC 2- Non-Coastal (ACI 2, ACI 3)	1.135	37.844	86.377	Agro-economic capacity

ABS: Access to Basic Services Indicator; ASTI: Assets Indicator; SSNI: Social Safety Net Indicator; ACI: Adaptive Capacity Indicator.

Table 3
Resilience capacity of farm households in coastal (Kendrapara) and non-coastal (Dhenkanal) districts.

Sl. No.	Farm livelihood group	Index value		t/z statistic
		Kendrapara district (n = 100)	Dhenkanal district (n = 100)	
1.	Farmers occupied with crop farming	59.52	44.20	4.638*
2.	Farmers occupied with livestock farming	32.83	27.34	1.464
3.	Farmers occupied with both crop+livestock farming	66.39	66.98	−0.10
Overall Resilience Capacity		**54.22**	**45.38**	**2.836***

* significant at the 5 % level of significance.

crop farmers and the crop+livestock farmers in terms of resiliency in Kendrapara. Therefore, we can conclude that resiliency differed for livelihood groups in the Kendrapara district except for crop farmers and crop+livestock farmers, which have similar resilience capacities. Dhenkanal farmers differed among all the livelihood groups in terms of resilience capacity.

Thus, it is worth concluding that farmers with more than one source of livelihood are more resilient and thus less vulnerable to climatic vagaries than are those with a mono-sourced livelihood. As the pillars contributing to RCI for crop + livestock farmers performed better than the mono-sourced livelihood options like crop farmers and livestock farmers, it was inferential that livelihood diversification aided better resiliency of the households along with other determinants driving their resiliency. Additionally, it is important to note that the resiliency of farmers who depend solely on crop farming is greater than that of livestock farmers but also has greater climatic vulnerability. This finding leads to the conclusion that climate change has a greater direct impact

Table 4
ANOVA and Post Hoc Tests showing significant differences in the resilience capacity of different farmer groups in the coastal (Kendrapara) and non-coastal (Dhenkanal) districts.

ANOVA						
Resilience Capacity Index		Sum of squares	Df	Mean square	F	Sig.[#]
RCI of farm households in Kendrapara	Between groups	15,947.593	2	7973.797	28.197	0.000
	Within groups	27,430.483	97	282.788		
	Total	43,378.077	99			
RCI of farm households in Dhenkanal	Between groups	15,949.861	2	7974.931	28.189	0.000
	Within groups	27,442.261	97	282.910		
	Total	43,392.122	99			

Post Hoc Tests (Scheffe Test[1]): Multiple Comparisons					
Variables			Mean difference	Std. error	Sig.[#]
RCI of farm households in Kendrapara	Crop farmers group	Livestock farmers group	26.69004*	4.05625	0.000
		Crop+Livestock farmers group	−6.87436	4.39102	0.298
	Livestock farmers group	Crop farmers group	−26.69004*	4.05625	0.000
		Crop+Livestock farmers group	−33.56440*	5.04489	0.000
	Crop+Livestock farmers group	Crop farmers group	6.87436	4.39102	0.298
		Livestock farmers group	33.56440*	5.04489	0.000
RCI of farm households in Dhenkanal	Crop farmers group	Livestock farmers group	15.79807*	4.05712	0.001
		Crop+Livestock farmers group	−22.05873*	4.39196	0.000
	Livestock farmers group	Crop farmers group	−15.79807*	4.05712	0.001
		Crop+Livestock farmers group	−37.85680*	5.04598	0.000
	Crop+Livestock farmers group	Crop farmers group	22.05873*	4.39196	0.000
		Livestock farmers group	37.85680*	5.04598	0.000

[1] Applied in case of equal variance as evident from test of homogeneity of variance (Levene Statistic); Robust Tests of Equality of Means indicate significant Welch statistic and Brown-Forsythe statistic values in all cases. *significant at either 1 % or 5 %.[#]significance values rounded to three decimal places.

on and bears on crop farmers, so any policy and reform directive towards farmers must cater to a greater share of the needs of crop farmers, followed by other groups, for visible change and greater coverage.

3.2. CSA interventions and their effectiveness and implementation feasibility

The CSA interventions were assessed on the basis of their performance and implementation feasibility in a given farmer's context. The CSA interventions were selected for performance analysis through pilot survey and in-depth focused group discussions with the beneficiary farmers under the NICRA project. These interventions were broadly categorized as scientific and institutional interventions. Thus, a total of 12 and nine scientific CSA interventions were studied in coastal and non-coastal district, respectively. And five institutional interventions were assessed in each of the coastal and non-coastal districts. The scientific CSA interventions were introduced to farmers as technologies under natural resource management (NRM), crop farming and livestock farming. The effectiveness and upscaling potential of each intervention was derived in terms of CSAEI and CSAIF (Fig. 2). The top three prioritized scientific interventions perceived effective by coastal farmers were relay cropping of paddy-green gram, flood tolerant variety of paddy (Swarna Sub-1) and green manuring with dhanicha in paddy crop. Similarly, top three prioritized institutional interventions perceived effective by coastal farmers were community managed farm machineries through custom hiring centres (CHCs), fodder bank and seed production and storage (of paddy, green gram and black gram) by farmers' groups. For the non-coastal ecosystem, top three prioritized scientific interventions perceived effective by respondent farmers were appropriate intercropping (groundnut+arhar), ridge and furrow method of moisture conservation and introduction of new crops like groundnut. Similarly, top three prioritized institutional interventions perceived effective by non-coastal farmers were community managed custom hiring centres of farm machineries, agro-advisories based on Indian Meteorological Department (IMD) weather forecast and village weather observatory, and capacity building for mushroom production technology.

3.3. Interrelationships between resilience and CSA performance

Partial Least Squares-Structural Equation Modeling was done to delineate the relationships between the four pillars of resilience, farm household resilient capacity, and CSA performance.

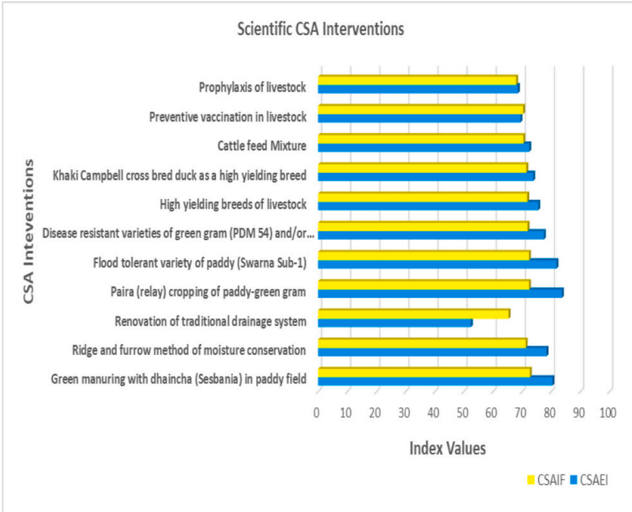
3.3.1. Assessing the reliability of the measurement model

The quality of the constructs can be inferred from the measures of reliability and validity. As per the procedural guidelines of PLS-SEM, the average variance extracted (AVE) was used to ensure the reliability of the selected constructs coupled with the outer loading values of the indicators of the constructs. After progressively removing the indicators not contributing at least 50 % of the variance, the reliability level was achieved (Table 5).The color-coded AVE values suggest that for the coastal district (Kendrapara), most of the formative indicators are reliable, as the AVE values are above 0.5 except for the pillar ABS, which is marginally less than 0.5; however, the AVE values for all the pillars in the noncoastal district suggest perfect reliability from all the pillars/constructs contributing to household resilience.

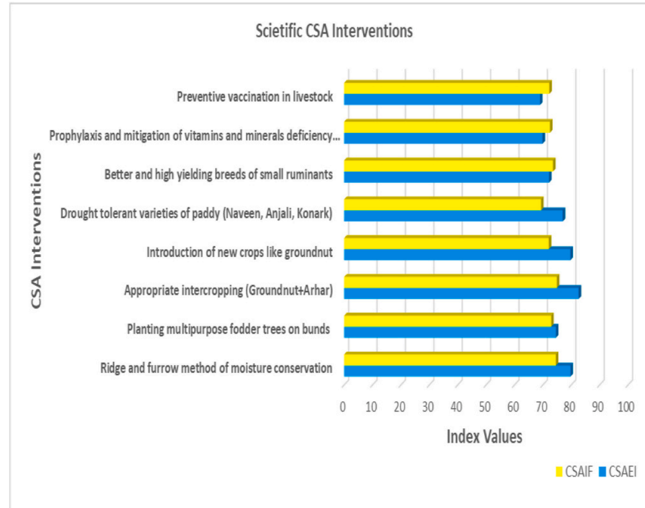
The validity of the indicators was established in the present study using discriminant validity, which ascertains the distinctiveness of the constructs in the study in terms of their individual identity and non-correlation with any other constructs. For the present study, using SMART PLS, discriminant validity was established by the Fornell–Larcker criterion of diagonal numbers. Table 5 suggests that the constructs considered for identifying the latent variable of the present model are valid because the square root values of the AVE for a particular construct are greater than its correlation with all the other constructs for both coastal and coastal districts.

3.3.2. Assessing the structural model

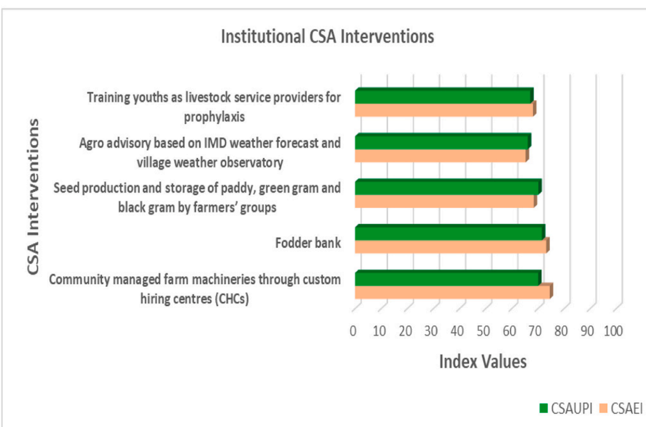
The structural models were assessed using t statistics (Table 6). In the case of the coastal environment, the AC and SSN constructs had statistically significant contributions to resiliency (R) [at 99 % and 90 % confidence levels]. In the case of a non-coastal environment, all the exogenous constructs, i.e., ABS, AC, AST, and SSN, had statistically significant contributions to resilience (R) [at 99 % and 90 % confidence



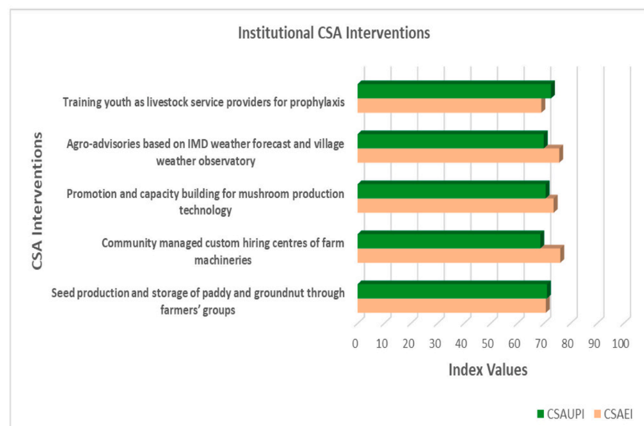
a. Scientific CSA interventions in Coastal district (Kendrapara)



c. Scientific CSA interventions in Non- Coastal district (Dhenkanal)



b. Institutional CSA interventions in Coastal district (Kendrapara)



d. Institutional CSA interventions in Non- Coastal district (Dhenkanal)

Fig. 2. Scientific CSA Interventions (a & b) in coastal (Kendrapara) and Institutional CSA interventions (c & d) in non-coastal (Dhenkanal) districts.

Table 5
Discriminant validity and reliability of resilience pillars using the Fornell–Larcker criterion.

District	Discriminant validity				Reliability
Kendrapara	ABS	AC	AST	SSN	Average Variance Extracted (AVE)
ABS	**0.683**				**0.466**
AC	−0.220	**0.779**			**0.607**
AST	−0.257	0.748	**0.746**		**0.542**
SSN	0.600	−0.226	−0.276	**0.779**	**0.607**
Dhenkanal					
ABS	**0.884**				**0.781**
AC	0.160	**0.829**			**0.687**
AST	0.203	0.785	**0.822**		**0.675**
SSN	0.172	−0.331	−0.209	**0.758**	**0.575**

levels, respectively]. The effect size of each exogenous construct was measured through the f^2 value (f^2values up to 0.20, > 0.15, and > 0.35, respectively represent small, medium, and large effect size). Value less than 0.02 indicates no effect. In the case of non-coastal district i.e., Dhenkanal, AC and SSN had medium effects on resilience (R). The R^2 and blindfolding-based cross-validated redundancy measure Q^2 of the final model for coastal and non-coastal setting have been presented in Table 6. The R square values of 0.75, 0.50 and 0.25 can be considered substantial, moderate, and weak, respectively (Henseler et al., 2009; Hair et al., 2011), in explaining the formative indicators of the model. From Table 6, it can be inferred that the indicators explaining the endogenous variable household resiliency (R) are in the range of weak to moderate (R square value = 0.263) for coastal district. While for the non-coastal district, the R^2 is substantial to moderate (R-square value = 0.604) for the explanation of the effect of formative indicators on the latent variable household resiliency. This finding suggests that, for coastal farmers, their adaptive capacity to climate change over a period builds resiliency, while for non-coastal farmers, several exogenous factors contribute to building their household resiliency.

The climatically vulnerable agri-ecosystem's outcome- performance of CSA interventions, in terms of effectiveness and implementation feasibility, was worked out following farmers participatory prioritization framework (Das et al., 2022a, 2022b), and these were considered as endogenous constructs in the present model. The overall effect of the latent variables (household resiliency) on the endogenous constructs (Overall Climate Smart Agricultural Effectiveness Index and Overall Climate Smart Agricultural Implementation Feasibility Index) is accurately predicted in the structural model for that construct (Table 6). The

Table 6
Significance and relevance of the relationships in the final path model of coastal (Kendrapara) and non-coastal (Dhenkanal) districts.

District	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	t statistics (|O/STDEV|)	P values	Effect size (f^2)	R square adjusted	Q^2 predict
Kendrapara							0.263	0.217
ABS - > R	−0.167	−0.172	0.133	1.253	0.210	0.025		
AC - > R	0.352	0.336	0.108	3.267	0.001	0.077		
AST - > R	0.047	0.070	0.103	0.458	0.647	**0.001**		
SSN - > R	−0.156	−0.154	0.089	1.748	0.081	0.022		
Dhenkanal							0.604	0.580
ABS - > R	0.180	0.176	0.079	2.276	0.023	0.077		
AC - > R	0.422	0.415	0.108	3.922	0.000	**0.166**		
AST - > R	0.189	0.191	0.101	1.882	0.060	0.035		
SSN - > R	−0.333	−0.338	0.066	5.074	0.000	**0.244**		

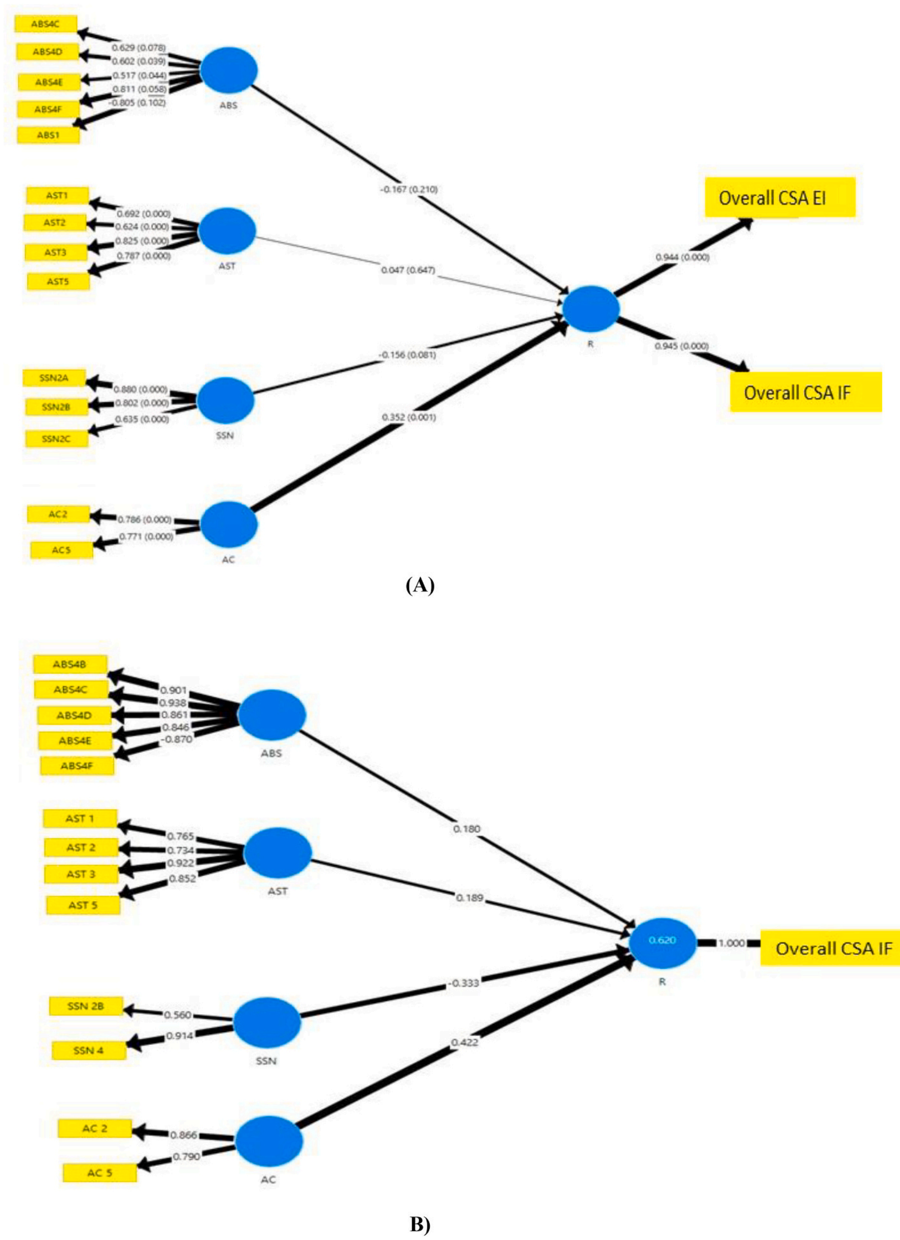


Fig. 3. Structural model for predicting household resilience (R) and its effect on (A) Climate Smart Agricultural interventions effectiveness (CSAEI) and their implementation feasibility (CSAIF) in the coastal district (Kendrapara), (B) Climate Smart Agricultural interventions implementation feasibility (CSAIF) in non-coastal district (Dhenkanal).

Q^2 values are larger than zero for the specific endogenous construct to indicate the predictive accuracy of the structural model for that construct (Sarstedt et al., 2017). Thus, the Q^2 values for Kendrapara (coastal district) had a smaller predictive relevance, while the Q^2 values for Dhenkanal (non-coastal district) had a large predictive relevance for the PLS-path model. Thus, it can be concluded from the above table that the model for the non-coastal district is a better fit with greater predictive relevance than the model for the coastal district. The same is diagrammatically explained through the models below (Fig. 3), with path coefficients and *p* values depicted above the arrows. The width of the arrows indicates the strength of the causal influence on the variable under study. The diagrammatic representation of household resilience capacity following the MIMIC model depicts the bearing of individual pillars or indicators of the resilience capacity of the household. It also delineates a better model of household resiliency in a contrasting ecosystem.

3.4. Determinants of farm household resilience

Multiple regression analysis following the backward elimination method between the livelihood indicators of Kendrapara farm households (Coastal district) and their resilience capacity (Table 7) revealed through 21 models that 8 livelihood indicators of farmers had a direct relationship with their resilience capacity. These factors included conveyance, water sources, road connectivity, participation in community initiatives, accessibility to common facilities, personal cosmopolite use, gross irrigated area, and size of water body, which together explained 75.4 % of the variation in resilience capacity ($R^2 = 0.754$).

Further, for the Dhenkanal district (Non-coastal district), regression analysis generated 23 models retaining 10 livelihood indicators of farm households that directly affected their resilience capacity. These variables were communication devices, conveyance, participation in community initiatives, annual family income, annual family expenditure, credit behavior, participation in training and extension, extent of suffering, landholding, and size of water body. Together, these factors explained 83.7 % of the variation ($R^2 = 0.837$) in the resilience capacity of the farmers in the Dhenkanal district.

The Durbin-Watson statistic of the regression model for both the districts was in the acceptable range of 1.5–2.5 (Statistic value for coastal district = 2.079 and non-Coastal district = 1.919), which indicates that there is no first-order autocorrelation and successive error differences are small among the independent variables. Further, the Variance Inflation Factor (VIF) was calculated to assess multicollinearity among independent variables and reported in Table 7. The VIF values for coastal district (Kendrapara) ranged from 1.450 to 2.757 and non-coastal district (Dhenkanal) ranged from 1.216 to 3.784, which is within the acceptable limit of $1 < \text{VIF} < 5$, thus ruling out the issue of multicollinearity. No variables had VIF values above the threshold of 5 in both the districts.

The direct, indirect, and intermediating effects of the livelihood indicators of farm households on resilience capacity in coastal and non-coastal districts are depicted through path diagrams drawn based on path analyses (Fig. 4). Path analysis of the relationships between livelihood indicators of Kendrapara farmers and their resilience capacity revealed that the greatest indirect effect was contributed by personal cosmopolite information sources use, followed by farm machinery and implements holding by the households. This indirect effect was substantially mediated by personal cosmopolite information sources use, followed by landholding and annual family expenditure. Interestingly, the personal cosmopolite information sources used by the farmers were also retained during the backward elimination regression technique; thus, emphasizing the livelihood indicator when addressing resilience capacity-related issues of farm households becomes necessary.

Similarly, from the path analysis indicating the effects of livelihood indicators on the resilience of Dhenkanal farmers, the maximum indirect effect was attributed to annual family income followed by the use of personal cosmopolite information sources use. The substantial indirect effect was mediated by gross irrigated area followed by landholding and annual family income. Landholding and annual family income were also retained in the backward elimination regression technique, thus constituting an inclusive variable for any future line of research studies and part of policy advocacy on resiliency.

Table 7
Multiple regression (backward elimination method) between livelihood indicators and resilience capacity of farm households in coastal (Kendrapara) and non-coastal (Dhenkanal) districts.

Model summary (Coastal district - Kendrapara)	Beta coefficient	Standard error	t value	Significance	VIF values
Constant	14.166	5.832	2.429	0.017	–
Conveyance	0.209***	0.075	3.264	0.002	1.646
Water sources	0.136*	0.061	1.693	0.094	2.552
Road connectivity	0.132**	0.058	2.162	0.033	1.450
Participation in community initiatives	0.185***	0.079	2.883	0.005	1.517
Accessibility to common facilities	0.137**	0.054	2.226	0.029	1.389
Personal cosmopolite information sources use	0.240***	0.065	3.835	0.000	2.334
Gross irrigated area	0.227***	0.067	3.232	0.002	2.757
Size of water body	−0.326***	0.083	−4.303	0.000	1.644

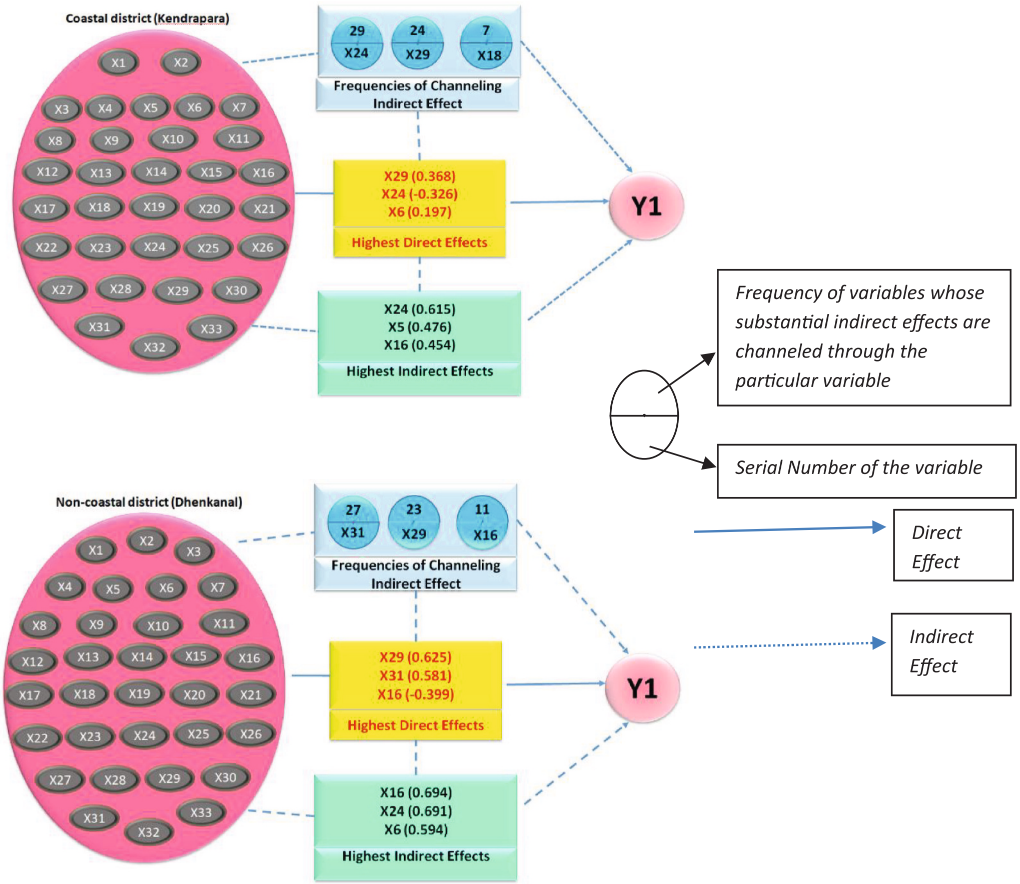
n = 100, F value = 24.515**, R value = 0.868, R square value = 0.754, Durbin-Watson statistic value = 2.079; $*p \le 0.1$, $** \le 0.05$, $*** \le 0.01$

Model summary (Non-coastal District - Dhenkanal)	Beta coefficient	Standard error	t value	Significance	VIF values
Constant	0.070	5.369	0.013	0.990	–
Communication devices	0.134**	0.058	2.089	0.040	2.275
Conveyance	−0.123*	0.066	−1.703	0.092	2.644
Participation in community initiatives	0.096*	0.042	1.699	0.093	1.310
Annual family income	−0.414***	0.100	−3.390	0.001	1.422
Annual family expenditure	0.229***	0.031	3.788	0.000	1.999
Credit behavior	0.284**	0.122	2.446	0.016	2.293
Participation in training and extension	−0.116**	0.069	−2.444	0.017	3.784
Extent of suffering	0.341***	0.085	3.989	0.000	1.634
Land holding	0.230***	0.053	4.290	0.000	2.280
Size of water body	0.574***	0.046	8.963	0.000	1.216

n = 100, F value = 40.998**, R value = 0.915, R square value = 0.837, Durbin-Watson statistic value = 1.919; $*p \le 0.1$, $** \le 0.05$, $*** \le 0.01$

4. Discussion

Climate change drives several climate smart agricultural development aspects (CSA interventions); however, a certain degree of uncertainty is attached to climate change. This uncertainty can be reduced if rightly the indicators of resiliency of farm households are addressed at the policy level. The present study attempts to discuss those resilience indicators using the RIMA II framework for a comprehensive idea of household resiliency and its relation with the CSA performance in



Legend:

Livelihood indicators under five livelihood assets of farm household (Independent variables)				
Physical assets:	*Social assets:*	*Financial assets:*	*Human assets:*	*Natural assets:*
X1-House type X2-Communication devices X3-Electricity connection X4-Conveyance X5-Farm machinery and implements X6-Water source X7-Road connectivity X8-Sanitation facility X9-Cooking facility	*X10-Social recognition X11-Social participation X12-Social cohesiveness X13-Participation in community initiatives X14-Accessibility to common facilities*	*X15-Economic status X16-Annual family income X17-Sources of income X18-Annual family expenditure X19-Household savings X20-Credit behavior X21-Insurance facilities*	*X22-Education level X23-Mass media use X24-Personal cosmopolite information sources use X25-Personal localite information sources use X26-Information availability X27-Participation in training and extension X28-Extent of suffering during calamities*	*X29-Land holding X30-Gross cultivated area X31-Gross irrigated area X32-Livestock holding X33-Size of water body*
Y1- Resilience capacity of farm households (Dependent variable)				

Fig. 4. Path diagrams showing the direct and indirect effects of livelihood indicators on the resilient capacity of farm households in coastal (Kendrapara) and non-coastal (Dhenkanal) districts.

climatically most vulnerable coastal and non-coastal regions in a developing nation like India. A study by Engle et al. (2014) has suggested that the development of resilience indicators and their application using dialog within and between communities adapting these indicators is crucial for future policy advocacy and utility for multiple stakeholders, such as banks, agencies and other organizations, who aim for a coordinated effort to attain better adaptation and resiliency. Beitnes et al. (2022) suggested that to enhance buffer capacity or resiliency, crucial roles are played by indicators such as informal and formal networks, access to outfield resources and governmental support.

Evidently from the present study, there is a contrast between coastal and non-coastal ecosystem while determining the resilience pillars (ABS, AST, SSN, and AC) from observed variables. It is important to note that household resiliency is a function of individuals, infrastructure and the institutional environment. In contrast, vulnerability is only a function of individuals and the livelihood environment. According to the present study, the RSM that is derived from resiliency pillars from observed variables is unique for each ecosystem. RSM of farm households in coastal region include market & transport infrastructure, access to health facility and access to primary school and drinking water under ABS, agricultural assets holding and stationary & livestock assets holding under AST, financial safety nets and social reliability network under SSN; and socio-economic capacity under the AC pillar. Similarly, in the non-coastal region, distance to market & infrastructure management under ABS, farm assets holding and livestock assets holding under AST, financial & social nets, and the formal transfers & safety net programmes under SSN. Educational level of household head and agro-economic capacity under AC are found in the resilience structure of farm households. In the present study, the individual, infrastructural and institutional factors affecting household-level resilience are delineated. Research studies by many researchers (Tol et al., 2007; Shah et al., 2013) suggest that proper access to facilities such as electricity and sanitation indicates preparedness against disasters and biohazardous diseases. To increase the resilience of impoverished households, safety nets combined with measures to generate income or acquire assets may be very effective (Abay et al., 2022). Food security outcomes are also affected by social networks and market integration (Bazzana et al., 2022). The RSM of climatically vulnerable coastal and non-coastal regions act as the precursors of the grass-root level policy advocacy for farm households to tackle the climate change consequences.

The resilience capacity of farmers with two sources of income (such as crop+livestock farmers) was greater than that of farmers with a single source of livelihood. The crop farmers in both coastal and non-coastal district were having better resiliency than that of the livestock farmers in the respective districts. This may be attributed to the better contributions of the variables under the four resiliency pillars (ABS, AST, SSN, AC) towards the resilience capacity (RCI) of the crop farmers' than the livestock farmers. The overall resilience capacity of coastal farmers was better than that of non-coastal farmers. It is evident that the major climate resilient initiatives and programs were targeted in the coastal regions of the Odisha state and the efforts of ICAR through the research interventions and capacity building initiatives are introduced through ICAR research institutes and KVKs. The coastal regions have received such interventions in the form of climate smart technologies and extension advisory services, while the non-coastal region have received it only in the form of limited research support through the projects implemented by the ICAR research institutes. Thus, it is pertinent to conclude that the need for an effective extension advisory service along with quality climate smart research interventions have a bearing on the better resilience capacity of coastal farmers than non-coastal farmers. In Bangladesh, which has similar ecosystems, crop farmers have attained resilience mainly through the growth of resistant varieties (location-specific stress-tolerant varieties and submergence-tolerant rice varieties) (Bairagi et al., 2021). According to Jha et al. (2021), agricultural practices, along with allied activities such as livestock rearing, ownership of hybrid livestock and more farmland, have aided the income source contributing to the restorative (adaptive) capacity of the farmers.

The resiliency of crop farmers was significantly different from that of livestock farmers in coastal districts. The livestock farmers were significantly different from both the crop farmers and the crop+livestock farmers in terms of resiliency in coastal districts. Therefore, we can conclude that resiliency differed for livelihood groups in coastal districts except for crop farmers and crop+livestock farmers, which have similar resilience capacity. Non-coastal farmers differed among all the livelihood groups in terms of resilience capacity. Several studies corroborate the importance of livelihood diversification (Poffenbarger et al., 2017; Huong et al., 2019; Carr, 2020), because, in the case of failure of one enterprise or livelihood option, livelihood diversification alone does not push farmers to distress, yet rather, they can revive their normalcy, which we refer to as resiliency. Crop+livestock integrated farming is more resilient against climate change-induced natural disasters than a specialized farming related to either crops or livestock (Seo, 2010). While integrated agricultural systems may be less vulnerable to the negative effects of climate change, farmers' adoption of integrated systems depends on their socio-economic and institutional conditions (Rufino et al., 2011). The findings of the present investigation are similar to those of Ghosh et al. (2017), who reported that the resiliency of farmers depends not only on the parameters related to agriculture but also on the socio-economic factors that drive these farmers into various strata. Thus, different strata of farmers exhibit different levels of resiliency. Stock et al. (2020) have suggested that for effective outcome of the CSA, national-level policies in India circling resiliency must consider the subnational or local-level needs of farmers, who differ in their social, political and financial resources. In their study, Beitnes et al. (2022) reported that long-term resiliency has to be politically and economically encouraged, and farmers need to exercise flexibility in using local resources. They suggested that the climate change adaptation processes have to be seen through a resilience lens.

According to present study, farmers' top aim in evaluating CSA performance is to increase revenue and farm output, followed by resilience and mitigation efforts. Prioritized CSA interventions include flood/drought tolerant paddy varieties, disease-resistant pulses, intercropping, moisture conservation, preventive vaccination, high yielding livestock breeds, cattle feed mixture, and prophylaxis for vitamin and mineral deficiency in livestock and poultry. These interventions can increase income and productivity while also creating climate resilient agriculture. Khatri-Chhetri et al. (2019) found that farmers in Maharashtra, India, are more concerned with the immediate benefits of CSA interventions than with developing resilience and mitigating emissions for future benefits, so productivity is given a high weightage followed by income, building a resilient agriculture system, and reducing agricultural emissions. According to Branca et al. (2021), implementing CSA technologies such as low tillage, crop residue assimilation, cover crops, and legumes leads to higher economic returns. Smallholder South African farmers prefer conservation agriculture, rainwater harvesting, drought-tolerant seed varieties, and early maturity; however, adoption of the first two CSA practices is low due to high initial costs and management intensity (Senyolo et al., 2018). Providing farmers with incentives for adaptation and mitigation advantages can be a management method for promoting a climate smart agricultural production system. Farmers have emphasized on institutional measures such as custom hiring facilities, seed banks, and farmers' clubs that need to be considered to bundling with scientific interventions for improved adoption of CSA by the farmers. In the present study feasibility of CSA practices is dependent on their alignment with government plans, cost, technical feasibility, and gender inclusivity, which are also indicated by Khatri-Chhetri et al. (2019). Institutional innovations are crucial for implementing scientific CSA technologies in practice. To successfully scale CSA, it is important to consider the farm household resilience along with the technologies, institutional measures and models in supportive contexts.

CSA has been emphasized as an effective strategy for improving the livelihoods of farm households with access to capital, strong social networks, and markets. The resilience level of farm households is related with the adoption of CSA interventions. The SEM indicates the significant and maximum bearing of AC on overall resilience followed by the SSN, while reflecting resilience effect on the CSA effectiveness and implementation feasibility in coastal region. In the non-coastal region, AC followed SSN and AST show the significant effect on resilience, showing a better predictive relational model with CSA implementation feasibility. Farmers with poor market connectivity gain less from CSA, which calls for policy advocacy for improving CSA adoption by increasing access to capital, marketing, and information networks (Bazzana et al., 2022). Further, farmers with wealthier backgrounds, better access to social/rural institutions and social capital tend to have higher adaptive capacity (Asfaw et al., 2016; Sardar et al., 2019) which ensures better adoption of CSA practices and technologies.

According to the sixth assessment report of the IPCC (2022), it is essential to construct resilient ecosystems in an integrated way that benefits people's livelihood, health, wellbeing and nutrition and contributes to disaster reduction and mitigation. In the present study, using multiple regression and path analysis, livelihood indicators such as personal cosmopolite information sources use and the education level of farmers in coastal ecosystems are found to significantly affect the resilient capacity of farm households. Thus, emphasizing these indicators when addressing resilience capacity-related issues becomes necessary. In contrast, in non-coastal ecosystem, livelihood indicators such as landholding, gross irrigated area, and gross cultivated area have maximum substantial indirect effects according to path analysis. In fact, the variable land holding are also revealed through the backward elimination regression technique, thus making it an inclusive variable for any future line of research or for policy advocacy on climate resilient farm households.

The findings of present study have re-ascertained that the attributes defining the resiliency of a farm household are subjective and external in nature. It is conclusive that purely external impositions (through incentives, subsidies, safety nets programs, etc.) do not drive the resiliency of farmers alone, nor are they purely subjective (through perceptive social, cultural, psychological elements, etc.) (Tyler et al., 2016; Jones and Tanner, 2017; Ogunbode et al., 2019). We emphasize that resilience-building is not limited to separating adaptation actions for individuals and communities; rather, it reconciles the different interests of collectively attempting resource needs, structural support and social cohesion, specifically addressing each stratum of farm households.

5. Conclusions and policy recommendations

The present research was carried out in one of the most climatically vulnerable states of India- Odisha, which is situated on the eastern coast. The aim of this study was to determine the resilience of major livelihood groups plying their farm activities in coastal and non-coastal ecosystem. Odisha, as a state, suffers from a multitude of contrasting climatic vagaries, such as cyclones, floods, droughts, and heatwaves. These climatic events at regular intervals have an overbearing impact on the livelihood of farm households through their income-generating activities; thus, farm households' resilience to climate change holds importance. This study, applying the Resilience Index Measurement and Analysis (RIMA II) framework, sheds light on the resilience of farm households and how it directly impacts their ability to adapt to climate change. The study highlights the crucial interlinkages between resilience determinants—access to basic services (ABS), household assets (AST), social safety networks (SSN), and adaptive capacity (AC)—and the effectiveness and implementation feasibility of climate-smart agriculture (CSA) interventions. Notably, coastal farmers have exhibited greater resilience capacity than their non-coastal counterparts, primarily due to targeted climate-resilient initiatives, improved extension services, and access to infrastructure and institutional support. Livelihood diversification, particularly integrating both crop and livestock farming, significantly enhances resilience, offering a buffer against climatic shocks. Additionally, access to market infrastructure, social safety nets, and adaptive capacity factors, such as education and information access, and availability of social and financial resources are among the major drivers determining the resilience of the farm households. In coastal regions, the ability to adapt, infrastructure connectivity, and the presence of strong community networks have played a key role in determining resilience; while in non-coastal regions, factors like landholding size, irrigation access, and financial security are more critical.

The relationship between resilience and CSA performance is undeniable. Structural equation modeling has established a strong relationship between household resilience and CSA performance. In coastal regions, AC and SSN are the most influential resilience pillars affecting CSA effectiveness and feasibility. Conversely, in non-coastal regions, three resilience pillars significantly contributed to household resilience, with AC, SSN, and AST demonstrating a higher predictive relationship with CSA adoption. This suggests that while coastal households benefit more from institutional and infrastructural support, non-coastal households require a broader approach that includes financial, social, and technical interventions.

To strengthen farm household resilience and improve the adoption of climate-smart agriculture, policymakers should focus on localized and targeted interventions. Expanding access to infrastructure, such as roads, markets, and irrigation systems, will enhance farmers' ability to respond to climate challenges. Financial incentives, including subsidies for climate-resilient technologies and low-interest credit programs, can encourage investment in CSA practices. Strengthening extension services and community-based training programs will empower farmers with the knowledge and skills needed for adaptive strategies. Additionally, improving access to social safety nets and insurance schemes will provide a crucial buffer against climate-induced shocks. Considering the climatic risks affecting different farm livelihood groups, mono-enterprises (crop or livestock) use to face significant losses and thus making adverse effects on farm households. Policymakers should also promote diversified farming systems that integrate crops and livestock, ensuring a more stable income source for farmers. The exploration of income-generating options in the non-farm sector to smoothen the impact of climate vagaries also holds importance in this context. To achieve this, extension functionaries should streamline training activities to promote livelihood diversification opportunities. Fostering collaboration between government agencies, research institutions, and local communities will create a more robust support network, ensuring that resilience-building efforts are sustainable and inclusive.

Ultimately, resilience is about more than just surviving climate change—it is about thriving despite it. Building resilience among farm households is a multifaceted process that necessitates a combination of institutional, infrastructural, and socio-economic strategies. Different farming communities face different challenges, and therefore, the solutions must be localized and inclusive. Policymakers must focus on enhancing market access, strengthening social networks, and promoting livelihood diversification to improve resilience. The adoption of CSA interventions must be complemented by robust extension services, financial support mechanisms, and participatory decision-making to ensure sustainability. With the right support and policies, farm households can build a future where they are not just reacting to climate shocks but proactively shaping a more secure and sustainable agricultural landscape. This research provides a framework for future studies and policy recommendations are aimed at enhancing climate resilience in vulnerable farming communities, ultimately contributing to sustainable climate smart agricultural development in developing nations.

Present study stands as a crucial cornerstone for empirical based decision making to address resiliency related issues. However, due to the complex nature of the households, multi-dimensional latent variable like resiliency needs more structured combination of quantitative & qualitative evidence wherein RIMA II framework is presently limited to quantitative mode only. Since the database is limited to a cross section, despite the demanding quantitative assessment of the construct, the study is open for future applications to similar livelihood groups. Also, livelihood strategies are unique to a specific livelihood group, thus, making it ethically coercive to impose upon any single model of resilience index across the entire farming fraternity.

Financial interests

The authors declare that they have no financial interests.

CRediT authorship contribution statement

Usha Das: Conceptualization. **M.A. Ansari:** Writing – review & editing, Conceptualization. **Souvik Ghosh:** Methodology, Formal analysis. **Neela Madhav Patnaik:** Writing – review & editing. **Saikat Maji:** Writing – review & editing, Methodology.

Compliance with ethical standards

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Declaration of competing interest

The authors have no competing interests to declare that they are relevant to the content of this article.

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Appendix A. Supplementary data

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Data availability

Data will be made available on request.

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