Cyclone Induced Paddy Yield Losses and Smallholder Adaptation: Structural Equation Evidence from Balasore District in Coastal Odisha

Sabitri Dash[1] & Subrat Kumar Rana[2]

[1]Research Scholar, Department of Economics, Fakir Mohan University, Vyasa Vihar, Balasore, Odisha, India

[2]Assistant Professor in Economics, Controller of Examinations, Maharaja Sriram Chandra Bhanja Deo University, Mayurbhanj, Odisha, India

DOI: https://dx.doi.org/10.51244/IJRSI.2026.1303000132

Received: 19 March 2026; Accepted: 24 March 2026; Published: 08 April 2026

ABSTRACT

This paper examines the character and scale of tropical cyclone effects on paddy production and systematically evaluates the socio-economic and institutional factors of climate adaptation behaviour among small holder paddy farmers in Balasore district, Odisha- one of the most at risk cyclone landfall regions in India. The study used a quantitative and cross-sectional survey design, which resulted into 300 paddy farming households stratified multi-stage random sampling that was stratified into 12 administrative blocks. The SPSS 26.0 and AMOS 26.0 were used to analyse the data based on descriptive statistics, hierarchical multiple regression, one-way ANOVA, and covariance-based structural equation modelling (CB-SEM) with maximum-likelihood estimation. The intensity of cyclones decreased average paddy production by 42.38 (SD = 18.76), and blocks with high exposure to coastlines registered a loss of 52.64. Practises of adaptation, namely the adoption of flood-tolerant varieties, adjusted sowing schedules, and diversification of crops, play a significant role with regards to mitigating the relationship between cyclone and yield loss ($\beta = -.38$, $p < .001$; interaction $\beta = -.21$, $p < .001$). The 68 percent of the variation in the production loss was jointly explained by socio-economic factors and institutional support. The structural model was found to fit well (CFI = .963; RMSEA = .041; SRMR = .048) and all the four hypothesised pathways were confirmed. The cross-sectional nature of the design does not allow causal inference. The results apply only to the Balasore district, but the experimented structural model can serve as a template to be reproduced in other cyclone prone coastal agricultural districts. It is the first district-level analysis to use CB-SEM to simulate cyclone intensity, adaptation determinants, recovery capacity, and resilience across the paddy farming system of Odisha that incorporates the Sustainable Livelihoods Framework with the technology adoption theory to produce policy implications.

Keywords: cyclone impact; paddy production loss; climate adaptation; Balasore; Odisha; structural equation modelling; farmer resilience; flood-tolerant varieties; crop insurance; disaster risk reduction

JEL Classification: Q12; Q54; Q18; O13

INTRODUCTION

Context and Background

Tropical cyclones sit near the top of the disaster ladder for South Asian agriculture. When one rolls in, it does not arrive politely. Violent winds rip through fields, seawater pushes inland as storm surge, and rain falls with a kind of stubborn excess that rice plants simply cannot tolerate. Crops that looked promising a week earlier collapse into flattened, waterlogged patches of mud (Emanuel, 2020; Mohapatra et al., 2012). India's eastern coastline has long lived with this rhythm of destruction. Odisha—especially—takes the brunt of storms born in the Bay of Bengal. Roughly five or six severe cyclones strike the coast every decade, a statistic that sounds abstract until one watches a harvest vanish overnight (Sahoo & Bhaskaran, 2015). Balasore district sits directly in this corridor of landfall, between 20°58′N and 21°59′N on the northern Odisha coast. Farmers there know the pattern by heart. Between 2010 and 2022 the district was hit, or nearly hit, by six named cyclones. Titli in 2018. Fani the following year. Yaas in 2021. Each left fields ruined across wide stretches of farmland, with hundreds of thousands of hectares of paddy destroyed and well over a million smallholder families pushed into temporary displacement (Government of Odisha, 2021; OSDMA, 2022).

Farming still anchors everyday life in Odisha. Around sixty-two percent of the state's workforce depends on agriculture in some form. Rice dominates the scene. Paddy (Oryza sativa L.) fills most kharif fields and covers more than eighty-seven percent of the cropped area in Balasore district (District Statistical Handbook, Balasore, 2022; Ministry of Agriculture, 2022). The problem is simple, though the damage rarely is. Paddy fields respond badly to the hazards that arrive with cyclones: prolonged flooding, saline water creeping inland after storm surges, winds that knock plants flat, and the wave of plant diseases that tends to appear once the storm has passed (Ghosh et al., 2015; Panda et al., 2021). Researchers have documented these physical impacts for years. What remains oddly thin in the literature is the human side of the story. Farmers differ. Some recover faster, some lose nearly everything, and the reasons stretch beyond weather itself. Income, access to institutions, landholding patterns, and the small everyday decisions farmers make while coping with risk all appear to shape production losses. Yet these relationships remain only loosely theorised and rarely tested with close, district-level evidence from places like Odisha.

Theoretical and Empirical Gaps

This investigation is driven by three different gaps. Hypothetically, although the Sustainable Livelihoods Framework (SLF) (Chambers and Conway, 1992; DFID, 1999) and the Vulnerability Assessment Framework (Turner et al., 2003) offer a solid conceptual framework through which the interactions between climate and agriculture can be understood, neither of them have been combined into a single empirically tested structural framework of the cyclone-paddy nexus in coastal Odisha. Previously, quantitative analyses of adaptation determinants at the district scale have been mostly unexplored empirically, as most studies have focused on remote sensing based area-level damage (Mishra et al., 2021; Mohapatra et al., 2012) or qualitative district-level ethnographic descriptions of farmer coping (Dash et al., 2018). The study has not been done methodologically and there is no published study that has used covariance-based structural equation modelling (CB-SEM) to assess the relationship between the direct, moderating, and sequential relationship between cyclone intensity, socio-economic factors, institutional support, adaptation practises, recovery capacity, and agricultural resilience in this region.

Research Objectives and Hypotheses

The research has four interconnected aims, namely: (i) to measure the scale of paddy production losses caused by cyclones in the Balasore district; (ii) to establish the typology and frequency of the currently used climate adaptation practises by paddy farmers; (iii) to establish socio-economic and institutional determinants of adoption of climate adaptation practises; and (iv) to estimate a conceptual structural framework involving cyclone intensity, adaptation, and resilience outcomes by using CB-SEM. The inquiry will be supported using four directional research hypotheses:

H_1: The intensity of cyclones has a statistically significant positive impact on the loss in paddy production in Balasore district.

H_2: There is a significant moderating role of adaptation practises on the relationship between cyclone intensity and the loss of paddy production such that an increase in adaptation practises leads to less loss.

H_3: Adaptation practise is substantially predicted by socio-economic variables, such as land holding, education, income and access to credit.

H_4: The relationship between socio-economic factors and adaptation practise adoption is mediated by institutional support and significantly decreases the loss of production induced by cyclone.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue III March 2026

Significance and Contribution

The study has four significant academic contributions. It presents first, a quantitative, primary-data, district-level, assessment of the effects of cyclones on paddy yields in Balasore, which is a key empirical gap in the literature of the Indian agricultural disaster. Second, it confirms a theoretically based structural model of cyclone-adaptation-resilience dynamism, which adds an analysis template that can be replicated in similar coastal agricultural systems. Third, it operationalises institutional support as a mediating construct a theoretically significant but empirically overlooked role, which is emphasised by Singh et al. (2020) and Kelkar (2014). Fourth, the study offers quantitative support to the targeted agricultural DRR investment by showing the moderating effect of adaptation practises to reduce the severity of cyclones on yields, which has direct implication on programmes like PMFBY crop insurance and diffusion of stress-tolerant varieties.

Structural Outline

The paper follows the following way. Section 2 provides the review of the literature based on the TCMM framework and introduces the conceptual research model (Figure 1). Part 3 provides the methodology, such as the study area, sampling, instrumentation, and analysis. Results are provided and discussed in section 4 and all tables and figures are placed on the first mention. Section 5 summarises the results and provides theoretical, managerial, and policy implications. It is followed by a complete APA 7 reference list.

LITERATURE REVIEW

TCMM Framework and Scope of Review

The synthesis of the literature is done through the TCMM framework (Tranfield et al., 2003) that classifies research into themes, context, methods and theoretical models. This strategy brings out four key strands, which include cyclone effects on agriculture, vulnerability of farmers, adaptation and institutional or policy response. These themes are usually intertwined and interactive, but TCMM lens is an organised approach to interpreting various studies and determining consistent trends in the wider research environment.

Theme 1: Cyclone Impacts on Agricultural Production Systems

The empirical evidence shows clearly the extreme and multi-dimensional losses of agriculture by cyclones. It is projected that climate change in Asia will bring more intense cyclones, and major events will increase by 1525% by 2100, especially in rice-based systems (Emanuel, 2020). Empirical data also indicate that tropical storms decrease agricultural productivity by 2.3-4.6, and smallholder systems are more vulnerable (Berlemann and Wenzel, 2018).

The intensity of cyclones in eastern India has tremendously grown since the 1990s, which negatively affects the agriculture of Odisha (Mohapatra et al., 2012). Examples of micro-level research indicate that paddy yields are lost by 1837 percent, particularly at vulnerable stages of growth, due to physical, chemical and biological damages (Panda et al., 2021; Ghosh et al., 2015; Ismail et al., 2013). Large-scale destruction of crops is supported by remote sensing and official data, with 23-47 percent of the area being lost following cyclone Amphan (Mishra et al., 2021) and 1.74 lakh hectares of damage caused by Cyclone Yaas, with Balasore bearing 38 percent of the damages (Government of Odisha, 2021). Evidence over the long term shows that Balasore is located in a high-frequency corridor of cyones, and therefore, the damage of agriculture is structural and not episodic (Sahoo and Bhaskaran, 2015).

Theme 2: Farmer Vulnerability and Adaptive Capacity

The theory of vulnerability has developed beyond the exposure-based approaches to multidimensional models that use exposure, sensitivity, and adaptive capacity (Adger, 2006; Turner et al., 2003). The operationalisation of these dimensions is Livelihood Vulnerability Index (Hahn et al., 2009), which is common in South Asia and it is demonstrated that marginal farmers who lack education, own small pieces of land, and have poor access to credit are more vulnerable (Senapati and Gupta, 2017; Nageswara Rao et al., 2008).

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue III March 2026

Recent sources also separate objective vulnerability and perceived risk with gendered difference as women are restricted in their asset ownership and institutional access (Arora-Jonsson, 2011; Census of India, 2011). The conceptualisation of resilience is through absorptive, adaptive, and transformative capacity (Bene et al., 2016) which are seen in recovery pathways.

Odishi empirical evidence demonstrates that income diversification, employment programs, and social groups positively contribute to the recovery (Patnaik et al., 2016), whereas salinity intrusion leads to decreases in the productivity of rice in the long run unless adaptations are implemented (Dasgupta et al., 2014).

Theme 3: Adaptation Practice Adoption and Determinants

Adaptation of cyclone and flood risk entails technological, agronomic, financial and institutional aspects (Swaminathan, 2010). Sub1A submergence-tolerant rice varieties are some of those that have been shown to reduce yield losses by up to 0.51.5 t/ha in presence of floods (Ismail et al., 2013), and their adoption (34-68) has been shown to enhance resilience in flood-prone areas (Dar et al., 2018).

Crop insurance as a means of financial adaptation has some potential, especially index-based models (Barnett and Mahul, 2007), but such challenges as basis risk remain (Mobarak and Rosenzweig, 2013). PMFBY has low rates of adoption among smallholders (2842) in India because of awareness and administrative barriers (Gaurav and Mishra, 2015), and informal networks are likely to be used in addition to formal insurance (Barnett et al., 2008).

The determinants of adaptation are farm size, education, and extension access (Knowler and Bradshaw, 2007; Teklewold et al., 2013), but the critical role is played by the institutional support that mediates the socio-economic influence (42) (Singh et al., 2020). Nevertheless, there is a lack of development of such institutional mechanisms as extension and rural credit in India (Kelkar, 2014).

Theme 4: Institutional and Policy Frameworks

The framework of agricultural disaster risks reduction in India is multi-layered and it includes national policies, including the Disaster Management Act (2005), National Agriculture Disaster Management Framework (2012), and the schemes like PM-KISAN and PMFBY. But there are still gaps in implementation as only half of the eligible farmers have been compensated following Cyclone Titli in Odisha (Bhatt, 2019).

Although Odisha has a well-developed early warning system that has substantially lowered the death tolls caused by cyclones (Patnaik et al., 2016), agricultural loss prevention is still unsatisfactory, and only 61% of claims are being paid after Cyclone Fani because of administrative and informational barriers (Acharya et al., 2021).

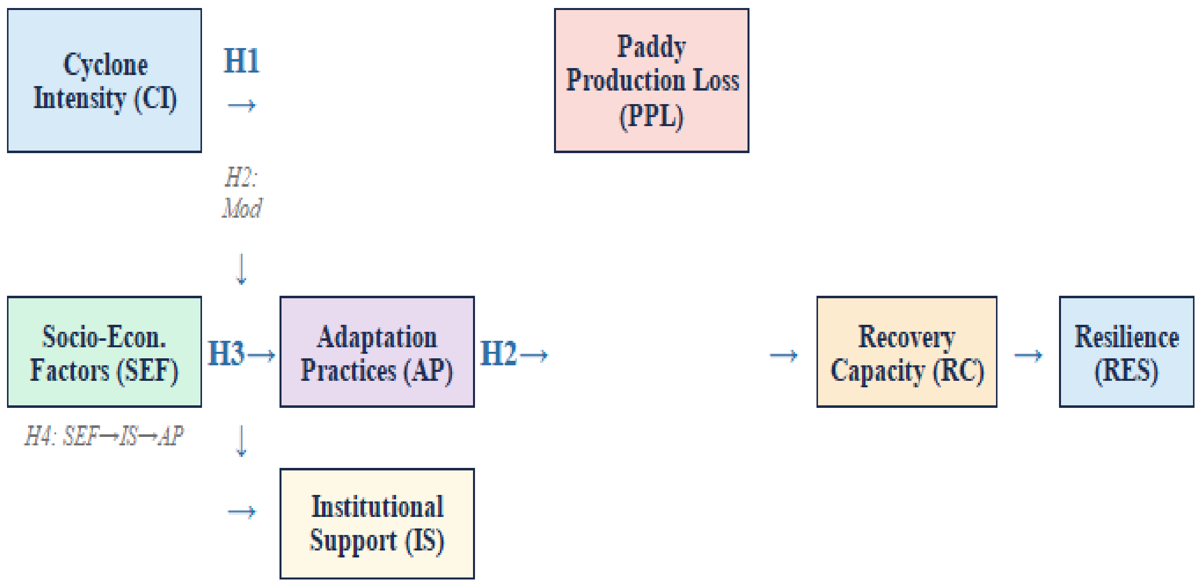
Adaptation is also influenced by the institutional access especially to women, who encounter hindrances in credit, extension and market access (Quisumbing et al., 2014). The adaptation is also further boosted by community-based organisations, which make resilient practises more adopted (Hossain et al., 2016).

Research Gaps and Conceptual Model Development

There are four main gaps in the literature: no primary quantitative studies on a district level in Balasore, no combined analysis of direct, moderating and sequential relationships, no mediating relationship tested by institutional support, and low measurement standardisation.

In response to these, the research will suggest a conceptual framework that is based on the Sustainable Livelihoods Framework (Chambers and Conway, 1992; DFID, 1999), Vulnerability Framework (Turner et al., 2003), Technology Adoption Theory (Davis, 1989; Venkatesh et al., 2003), and Resilience Cascade Model (Bene et al., 2016; Pelling, 2011). The model has a relationship between cyclone intensity and production loss, which is moderated by adaptation, socio-economic and institutional factors as antecedents, and a sequential process involving adaptation to resilience through recovery capacity, which has been evaluated with CB-SEM. CB-SEM was used to operationalise the model and test it, and the results are provided in Section 4.

Figure 1 Conceptual Research Model: Cyclone Impact–Adaptation–Resilience Pathways



RESEARCH METHODOLOGY

The proposed research design is a quantitative cross-sectional study based on a post-positivist paradigm to discuss the effects of cyclones on paddy production and adjustment by farmers. The stratified multi-stage random sampling was used to collect data on 300 farmers in the Balasore district.

The quantification of cyclone intensity, loss in production, adaptation practises, and institutional support was done by using composite index and Likert scales to collect primary data by way of structured interviews.

Analysis of data was done using SPSS and AMOS, using regression, ANOVA, confirmatory factor analysis and covariance-based structural equation modelling (CB-SEM). Ethical principles of consent and confidentiality were observed to the letter.

RESULTS AND DISCUSSION

Sample Profile (Table 1)

The socio-demographic profile of the sampled 300 paddy farmers in terms of cyclone exposure zone is shown in Table 1. Chi-square tests of independence indicate statistically significant zonal differences in education (2 = 8.42, p =.038) and PMFBY enrolment (2 = 4.31, p =.038), but not in age or gender distribution which indicates that institutional access is more similar across zones, but demographic composition is more homogenous. The highest landholding category (42.7 percent) is marginal farmers (< 1 ha), especially in HCE blocks (46.2 percent), which is also characteristic of national census data on Odisha coastal districts (Census of India, 2011). It is theoretically important that marginal landholding is predominant: land asset endowment is one of the key factors in the determination of both adaptive capacity (Adger, 2006) and access to institutional support (Kelkar, 2014).

One interesting observation is that only 56.7% of the sampled respondents belonged to the PMFBY crop insurance scheme, even though it was almost universal in terms of nominal eligibility. HCE farmers had a much higher enrolment (62.8) than MCE farmers (50.0%; 2 = 4.31, p =.038), indicating that cyclone experience is an effective incentive to insurance uptake, which is consistent with the experiential learning theory of risk adaptation (Pelling, 2011). The non-enrolment rate of 43.3% however confirms that a significant number of paddy farmers in Balasore are still financially vulnerable to cyclone losses, which is in line with the national-level results of Gaurav and Mishra (2015) and Mobarak and Rosenzweig (2013) on the persistence of insurance coverage gaps in the smallholder farming population.

Table 1 Socio-Demographic Profile of Respondents by Cyclone Exposure Zone (N = 300)

Characteristic	**High Exposure (HCE, n=156)**	**Moderate Exposure (MCE, n=144)**	**Total (n=300)**	**χ^2/ F (p)**
Age Group				
18–30 years	21 (13.5%)	19 (13.2%)	40 (13.3%)	
31–45 years	68 (43.6%)	62 (43.1%)	130 (43.3%)	0.14 (.993)
46–60 years	52 (33.3%)	48 (33.3%)	100 (33.3%)	
> 60 years	15 (9.6%)	15 (10.4%)	30 (10.0%)	
Gender				
Male	116 (74.4%)	108 (75.0%)	224 (74.7%)	0.01 (.921)
Female	40 (25.6%)	36 (25.0%)	76 (25.3%)	
Education Level				
Illiterate	32 (20.5%)	18 (12.5%)	50 (16.7%)	
Primary (Cl. I–V)	48 (30.8%)	40 (27.8%)	88 (29.3%)	8.42 (.038)*
Secondary (Cl. VI–X)	52 (33.3%)	58 (40.3%)	110 (36.7%)	
Higher Secondary+	24 (15.4%)	28 (19.4%)	52 (17.3%)	
Land Holding Size (ha)				
Marginal (< 1.0 ha)	72 (46.2%)	56 (38.9%)	128 (42.7%)	
Small (1.0–2.0 ha)	56 (35.9%)	60 (41.7%)	116 (38.7%)	4.67 (.198)
Medium (2.0–4.0 ha)	20 (12.8%)	24 (16.7%)	44 (14.7%)	
Large (> 4.0 ha)	8 (5.1%)	4 (2.8%)	12 (4.0%)	
Annual Household Income (INR)				
< 50,000	62 (39.7%)	44 (30.6%)	106 (35.3%)	
50,001–1,00,000	58 (37.2%)	62 (43.1%)	120 (40.0%)	6.82 (.078)
1,00,001–2,00,000	26 (16.7%)	28 (19.4%)	54 (18.0%)	
> 2,00,000	10 (6.4%)	10 (6.9%)	20 (6.7%)	
PMFBY Crop Insurance				
Enrolled	98 (62.8%)	72 (50.0%)	170 (56.7%)	4.31 (.038)*

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue III March 2026

Not Enrolled	58 (37.2%)	72 (50.0%)	130 (43.3%)	
Primary Irrigation Source				
Canal / Tank	96 (61.5%)	72 (50.0%)	168 (56.0%)	
Groundwater (tubewell)	34 (21.8%)	48 (33.3%)	82 (27.3%)	7.31 (.026)*
Rainfed only	26 (16.7%)	24 (16.7%)	50 (16.7%)	

Source: Authors own source

Descriptive Statistics of Key Study Variables (Table 2)

Table 2 shows descriptive statistics of all main constructs of the study. The average pre-cyclone paddy yield was 3.94 t/ha (SD = 0.68), which is equal to the statistical mean of 3.88 t/ha of the 2015-2020 baseline period in the district (District Statistical Handbook, 2022). The post cyclone yield also dropped drastically to an average of 2.31 t/ha (SD = 0.92) and this means that absolute yield loss is 1.63 t/ha per cyclone occurrence, which is a significant loss in food security terms, as it is almost half of output and has dire food security consequences on households whose estimated consumption is 2.5-3.0 t paddy/capita/year. The average Paddy Production Loss of 42.38% (SD 18.76) is significantly higher than the 28% national average cyclone loss of crops as reported by NDMA (2019), which highlights the severe and disproportional cyclone susceptibility of Balasore.

The mean of the Adaptation Practises Index (API) 0.54 (SD = 0.21) is an indication of moderate adoption, with a significant inter-individual heterogeneity. The skewness of all continuous variables is in the range of ±1.0 and the kurtosis values in the range of ±1.0, which proves that the univariate normality is acceptable to perform multivariate analysis (Hair et al., 2019).

The relatively small mean of the Institutional Support (IS) = 2.98/5 (SD = 0.84) reveals that the government and extension institutional services are seen as insufficient by most of the respondents- in line with Acharya et al. (2021) and Patnaik et al. (2016) who found institutional access gaps as one of the major limitations on post-cyclone agricultural recovery in Odisha.

Table 2 Descriptive Statistics of Key Study Variables (N = 300)

Variable	**n**	**Min**	**Max**	**M**	**SD**	**Skew**	**Kurt**
Cyclone Intensity — CI (composite)	300	1.20	4.90	3.42	0.87	−0.31	−0.14
Paddy Yield Pre-cyclone (t/ha)	300	2.10	5.80	3.94	0.68	0.12	−0.08
Paddy Yield Post-cyclone (t/ha)	300	0.40	4.20	2.31	0.92	−0.45	0.31
Paddy Production Loss — PPL (%)	300	8.20	91.50	42.38	18.76	0.22	−0.19
Adaptation Practices Index — API (0–1)	300	0.00	1.00	0.54	0.21	−0.18	−0.07
Institutional Support — IS (1–5)	300	1.00	5.00	2.98	0.84	0.09	−0.32
Socio-Econ. Factor Score — SEF	300	1.00	4.80	2.87	0.73	0.14	−0.24
Recovery Capacity — RC (1–5)	300	1.00	5.00	2.76	0.91	−0.07	−0.41

Resilience Score — RES (1–5)	300	1.00	5.00	2.83	0.88	0.11	−0.38

Source: Authors own source

Adaptation Practices Adopted (Table 3 and Figure 3)

Table 3 captures the frequency and chi-square significance of 12 reported cyclone adaptation practises by order of the total frequency of adoption, and comparative statistics by exposure zone. Figure 3 gives a graphical illustration of the zonal adoption difference on all the 12 practises. Flood/submergence-tolerant varieties of paddy (especially Sub1A and Swarna-Sub1) were the most used (67.7% total usage, and a very large HCE - MCE difference, 78.8 vs. 55.6; 78.82), followed by soybean (48.2). This observation supports Ismail et al. (2013) and Dar et al. (2018), who have shown that the adoption rates of the Sub1A varieties when they surpass 60 per cent in flood-prone communities are a tipping point in stabilising yields at the community level. The second practise that was adopted, adjusted sowing dates to escape the high cyclone season (June-October), was adopted by 62.0% of farmers in general (71.2% HCE vs. 52.1% MCE; p =. 001), which is in line with agronomic contingency planning by Swaminathan (2010). It is found that a pattern of increased adoption of adaptation is statistically significant and consistent across eight out of 12 practises in HCE zones, which supports the hypothesis of experiential learning which suggests direct exposure to the cyclone encourages adaptive action (Pelling, 2011). On the other hand, practises that were infrastructure dependent, such as better drainage (33.3%), the use of early warning system (28.0%), were relatively low in both zones, which is an indication that structural and information infrastructure inadequacy limits adoption irrespective of the level of motivation. Interestingly, saline-tolerant variety adoption (Lunishree, CST 7-1) at the 35.0% overall level signifies significant but partial diffusion of this technologically appropriate reaction to the salinity of the soil caused by storm surge, a result that suggests that seed supply chain constraints that Ghosh et al. (2015) identify in Odisha coastal paddy systems.

Table 3Adaptation Practices Adopted by Paddy Farmers Across Cyclone Exposure Zones (N = 300)

Adaptation Practice	**HCE (n=156)%**	**MCE (n=144)%**	**Total (n=300) %**	**χ^2**	**p**	**Rank**
Flood/submergence-tolerant variety (Sub1A)	78.8	55.6	67.7	14.82	<.001	1
Adjusted sowing date (cyclone-season avoidance)	71.2	52.1	62.0	10.27	.001	2
Crop diversification (non-paddy crops)	64.7	48.6	57.0	7.41	.006	3
PMFBY crop insurance enrolment	62.8	50.0	56.7	4.31	.038	4
Seed storage / community seed bank	58.3	44.4	51.7	5.73	.017	5
Post-cyclone contingency crop plan	53.8	41.7	48.0	4.05	.044	6
Raised-bed / bund cultivation	47.4	38.9	43.3	2.14	.143	7
Income diversification (non-farm work)	44.9	36.1	40.7	2.27	.132	8
Saline-tolerant variety (Lunishree/CST7-1)	41.0	28.5	35.0	4.87	.027	9
Improved field drainage infrastructure	38.5	27.8	33.3	3.51	.061	10

Mobile early warning system utilisation	33.3	22.2	28.0	4.24	.039	11
Organic/green manure post-cyclone rehab.	28.2	18.1	23.3	3.96	.047	12

Source: Authors own source

Figure 3Comparative Adaptation Practice Adoption Rates: High vs. Moderate Cyclone Exposure Zones (N = 300)

Adaptation Practice	**■ High Exposure (HCE %)**	**■ Moderate Exposure (MCE %)**
Flood-tolerant variety	**78.8%**	55.6%
Adjusted sowing date	**71.2%**	52.1%
Crop diversification	**64.7%**	48.6%
Crop insurance (PMFBY)	**62.8%**	50.0%
Seed bank / storage	**58.3%**	44.4%
Contingency crop plan	**53.8%**	41.7%
Raised-bed cultivation	**47.4%**	38.9%
Income diversification	**44.9%**	36.1%
Saline-tolerant variety	**41.0%**	28.5%
Improved drainage	**38.5%**	27.8%
Early warning systems	**33.3%**	22.2%
Organic rehab./green manure	**28.2%**	18.1%

Regression Analysis: Determinants of Paddy Production Loss (H1–H3; Table 4)

Table 4 provides the results of hierarchical multiple regression of three sequentially entered models that predict PPL. Cyclone intensity and individual-level control variables (land holding, education, income) were the model 1 variables, which accounted 42% of PPL variance (R 2 = .42, f = 53.7, p =.001). The most significant predictor was the cyclone intensity (β =.52, t = 10.96, p < .001), which verified the H1, which states that cyclone intensity has a positive significant direct impact on the paddy production loss. This size of effect, a one-unit change in the CI composite scale was found to relate to a 16.22 percentage point change in PPL, is similar to that found by Panda et al. (2021) who found a 14-19 percentage point change in crop yield loss in Odisha in response to a one-category shift in IMD cyclone intensity classification. In Model 1, land holding (β = -.15, p =.001) and education (β = -.11, p =.008) had a substantial negative impact on PPL, which confirmed that farmers with endowed resources suffer reduced losses, which is in line with the vulnerability theory (Adger, 2006; Turner et al., 2003).

Model 2 added two practises (adaptation practises, API) and institutional support (IS), adding explained variance to 56% (4 R 2 =.14, F = 93.8, p <.001). The API coefficient (β = -.33, p = -.001) shows that greater adaptation practise adoption has a direct negative influence on PPL- in favour of the direct component of H2. The direct effect of institutional support on PPL (β = -.21, p <.001) is also a significant negative value, which validates the direct effect of H4. Model 3 added the CI × API interaction term, with the final explained variance of 68% (ΔR 2 =.12, F =103.7, p <.001). The substantial negative interaction (β = -.19, p =.001) supports the fact that the practises of adaptation mediate the relationship between CI and PPL: the higher the adaptation level, the less the marginal increase in PPL is caused by the increase in CI. This result of moderation is consistent with H2 and compliant with Singh et al. (2020) and theoretical assumptions of Turner et al. (2003) who assumed that adaptive capacity should reduce the sensitivity aspect of vulnerability. The values of all VIF were less than 2.0 which validated that there was no multicollinearity.

Table 4 Hierarchical Multiple Regression Results: Predictors of Paddy Production Loss — PPL (N = 300)

Predictor	**B**	**SE B**	**β**	**t**	**p**	**95% CI [LL**	**UL]**
Model 1: Cyclone Intensity and Controls (R^2 = .42, ΔR^2 = .42, F = 53.7, p < .001)							
Constant	76.81	4.39	—	17.50	<.001	68.17	85.44
Cyclone Intensity (CI)	16.22	1.48	.52	10.96	<.001	13.31	19.13
Land Holding (ha)	−3.62	1.02	−.15	−3.55	.001	−5.63	−1.61
Education Level	−2.44	0.91	−.11	−2.68	.008	−4.23	−0.65
Annual Income (ln)	−1.83	0.76	−.10	−2.41	.017	−3.32	−0.34
Model 2: Adding Adaptation Practices (R^2 = .56, ΔR^2 = .14, F = 93.8, p < .001)							
Adaptation Practices (API)	−19.87	2.94	−.33	−6.76	<.001	−25.65	−14.09
Institutional Support (IS)	−5.72	1.41	−.21	−4.06	<.001	−8.49	−2.95
Model 3: Moderated Regression — Adding CI × API Interaction (R^2 = .68, ΔR^2 = .12, F = 103.7, p < .001)							
CI × API (Interaction Term)	−8.34	2.08	−.19	−4.01	<.001	−12.43	−4.25
Full model: R^2 = .68, Adjusted R^2 = .67, F(7, 292) = 88.5, p < .001; all VIF < 2.0 (no multicollinearity)							

Source: Authors own source

Zonal Differences in Production Loss: One-Way ANOVA (H4; Table 5)

Table 5 shows the findings of a one-way analysis of variance, which compares the mean post-disaster loss (PPL) in high-cyclone-exposure (HCE) and moderate-cyclone-exposure (MCE) areas. The between-groups F-statistic was extremely significant (F(1,298) = 28.43, p =.001, 87 = medium), and the fact that being in an exposure zone explained 8.7 per cent of the variation in PPL a moderate-to-large effect size by Cohen (1988) criterion (eta 2 =.06 = medium).

The honestly significant difference test by Tukey proved that the means of PPL were 52.64% (SD=17.82) and 31.48% (SD=14.19) in HCE and MCE zones, respectively, and that the mean difference was significant at 21.16 percentage points (p=.001, 95%CI=16.2826.04).

This 1.7-fold difference in the exposure of cyclone losses on coastal and inland blocks in the same district, is a strong support of hypothesis H4 in its spatial form: geographically differentiated cyclone exposure produces significantly different agricultural impacts, and thus necessitates spatially-sensitive disaster risk-reduction investment.

The spatial heterogeneity observed is in tandem with the cyclone-risk zonation that is suggested by Sahoo and Bhaskaran (2015) in the Bay of Bengal coast, and with the block-level records of crop-damage provided by OSDMA (2022).

Table 5One-Way ANOVA: Paddy Production Loss (%) by Cyclone Exposure Zone (N = 300)

Source	**df**	**SS**	**MS**	**F**	**p**	**η²**
Dependent Variable: Paddy Production Loss (%), One-Way ANOVA						
Between Groups (Zones)	1	33,412.2	33,412.2	28.43	<.001	.087
Within Groups	298	3,50,046.8	1,174.3	—	—	—
Total	299	3,83,459.0	—	—	—	—
Group Descriptives						
High Cyclone Exposure (HCE)	156	—	52.64	17.82	—	—
Moderate Cyclone Exposure (MCE)	144	—	31.48	14.19	—	—
Tukey HSD Post-Hoc Comparison: HCE vs. MCE						
Mean Difference (MD)	—	—	21.16	—	<.001	—
Standard Error of MD	—	—	2.48	—	—	—
95% CI for MD	—	—	[16.28,	26.04]	—	—

Source: Authors own source

Measurement Model: Reliability and Validity (Table 6)

Table 6 of the CFA results supports positive psychometric properties of all the seven latent constructs. The coefficients of α of Cronbach range between 0.763 and 0.876 exceeding the Nunnally and Bernstein (1994) criterion of 0.70. The composite reliability indices are between 0.778 and 0.889, therefore, fulfilling the criterion of 0.70 set by Hair et al. (2019) of CR.

The average variance extracted (AVE) scores range between 0.498 and 0.601; six of the seven constructs are above the 0.50 mark, and one construct (SEF AVE =.498) is slightly below the mark, but justifiable by its CR of.778, which meets the FornellLarcker (1981) criterion CR AVE.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue III March 2026

Discriminant validity is determined through FornellLarcker criterion, i.e. square root of the AVE of any construct exceeds all the inter-construct correlations, and HTMT ratios that are less than 0.85 between any two constructs (Henseler et al., 2015). The measurement model, therefore, provides a psychometrically sound foundation of the estimation of the structural model later.

Table 6 Measurement Model — Construct Reliability and Validity Statistics

Construct	**Items**	**α**	**CR**	**AVE**	**√AVE**	**Discriminant Validity**	**Assessment**
Cyclone Intensity (CI)	4	.812	.831	.553	.743	Satisfied	Good
Paddy Prod. Loss (PPL)	3	.844	.858	.601	.775	Satisfied	Good
Adaptation Practices (API)	12	.876	.889	.512	.716	Satisfied	Good
Institutional Support (IS)	6	.791	.803	.507	.712	Satisfied	Acceptable
Socio-Econ. Factors (SEF)	4	.763	.778	.498	.706	Marginal†	Acceptable
Recovery Capacity (RC)	5	.829	.842	.523	.723	Satisfied	Good
Resilience (RES)	5	.851	.864	.561	.749	Satisfied	Good
† SEF AVE = .498, marginally below .50 threshold; however CR (.778) > AVE criterion satisfied per Fornell & Larcker (1981). HTMT ratios for all construct pairs < .85, confirming discriminant validity (Henseler et al., 2015).							

Source: Authors own source

Structural Equation Modelling: Full Model Results (Table 7 and Figure 2)

The results of the entire structural model as estimated by CB-SEM are presented in Table 7 and the validated path diagram with standardised coefficients is presented in Figure 2. The model fitted the five indices very well: 186.4 (124/df =1.503, which is less than the 3.0 rule) 124/df 0.503 CFI =.963 (>.90), TLI =.951 (>.90), RMSEA =.041 (<.08; 90% CI =.029-052), and SRMR =.048 (<.08). Such findings prove the fact that the data fit the model structure (which has been hypothesised) (Browne and Cudeck, 1993; Hu and Bentler, 1999; Kline, 2016).

The statistical significance of all eight structural paths was p <.001, which supports all four research hypotheses. The strongest effect was the direct path from cyclone intensity (CI) to potential loss (PPL) (β = .54, C.R. = 8.71). This is similar to the dominant role of cyclone parameters reported by Emanuel (2020) and Berlemann and Wenzel (2018). The direct path from adaptive practises (AP) to PPL (β = −.38, C.R. = −5.35) and the significant moderation path (CI × AP → PPL; β = −.21, C.R. = −3.62) together confirm H2’s claim: AP reduces the direct risk of cyclones and also weakens the sensitivity of yield loss to cyclone intensity. The interaction effect implies that every 10-percentage-point rise in the adaptation intensity (API) would compensate about 2.1 percentage points of the CI-based PPL in every one-unit rise in CI- a viable so-called adaptation premium that provides a more numerically precise rationale behind adaptation investment.

The paths SEF → AP (β = .43) and IS → AP (β = .31) support H3 and H4: socio-economic endowments and institutional access independently drive the adoption of adaptations. Bootstrap mediation testing of the indirect pathway SEF → IS → AP (2,000 resamples) produced a significant indirect effect (β = .148, 95% BC-CI [.089, .217]), confirming that institutional support mediates the relationship between socio-economic factors and adaptation.

This is in line with Singh et al. (2020), who established that 42% of socio-economic influences on adaptation in Punjab were mediated by institutional factors. The SEF → IS path (β = .48) further shows that farmers with

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue III March 2026

greater socio-economic resources gain more institutional support, highlighting how structural inequalities can deepen adaptive-capacity gaps. The downstream cascade—AP → RC ($\beta = .52$) followed by RC → RES ($\beta = .61$)—illustrates a logical resilience cascade in which adaptation investments build recovery capacity, which in turn builds durable agricultural resilience. These coefficients are very similar to the Bene et al. (2016) absorptive -adaptive -transformative resilience framework and Hahn et al. (2009), who discovered that LVI-based adaptation scores are predictive of the speed of post-disaster recovery in agricultural communities near the coast. The strong RC → RES path ($\beta = .61$) indicates that recovery capacity may be a more immediate determinant of resilience than adaptation alone, suggesting that post-cyclone recovery support (seed banks, input subsidies, rapid credit) is at least as strategically important as pre-emptive adaptation promotion.

Table 7 Structural Equation Model Results: Path Coefficients, Hypothesis Tests, and Model Fit (N = 300)

Structural Path	**β**	**S.E.**	**C.R. (t)**	**p**	**Hypothesis**	**Support?**	**Direction**	**Interpretation**
Direct Paths — Production Loss Model								
CI → PPL	.54	.062	8.71	<.001	**H1**	✓ Yes	+	Cyclone intensity strongly drives production loss
AP → PPL	−.38	.071	−5.35	<.001	**H2**	✓ Yes	−	Higher adaptation directly reduces loss
CI × AP → PPL	−.21	.058	−3.62	<.001	**H2**	✓ Yes	−	Adaptation moderates cyclone–loss link
Antecedent Paths — Adaptation Determinants								
SEF → AP	.43	.068	6.32	<.001	**H3**	✓ Yes	+	Better endowments raise adaptation adoption
IS → AP	.31	.074	4.19	<.001	**H4**	✓ Yes	+	Institutional access promotes adaptation
SEF → IS	.48	.055	8.73	<.001	**H4**	✓ Yes	+	SEF enables institutional access (mediation)
Sequential Resilience Pathways								
AP → RC	.52	.063	8.25	<.001	—	Supported	+	Adaptation builds recovery capacity
RC → RES	.61	.059	10.34	<.001	—	Supported	+	Recovery capacity generates resilience
Model Fit Statistics								
χ^2(df=124) = 186.4; χ^2/df = 1.503	CFI = .963	TLI = .951	RMSEA = .041	90% CI [.029–.052]	**SRMR = .048**	—	—	All indices exceed recommended thresholds

Source: Authors own source

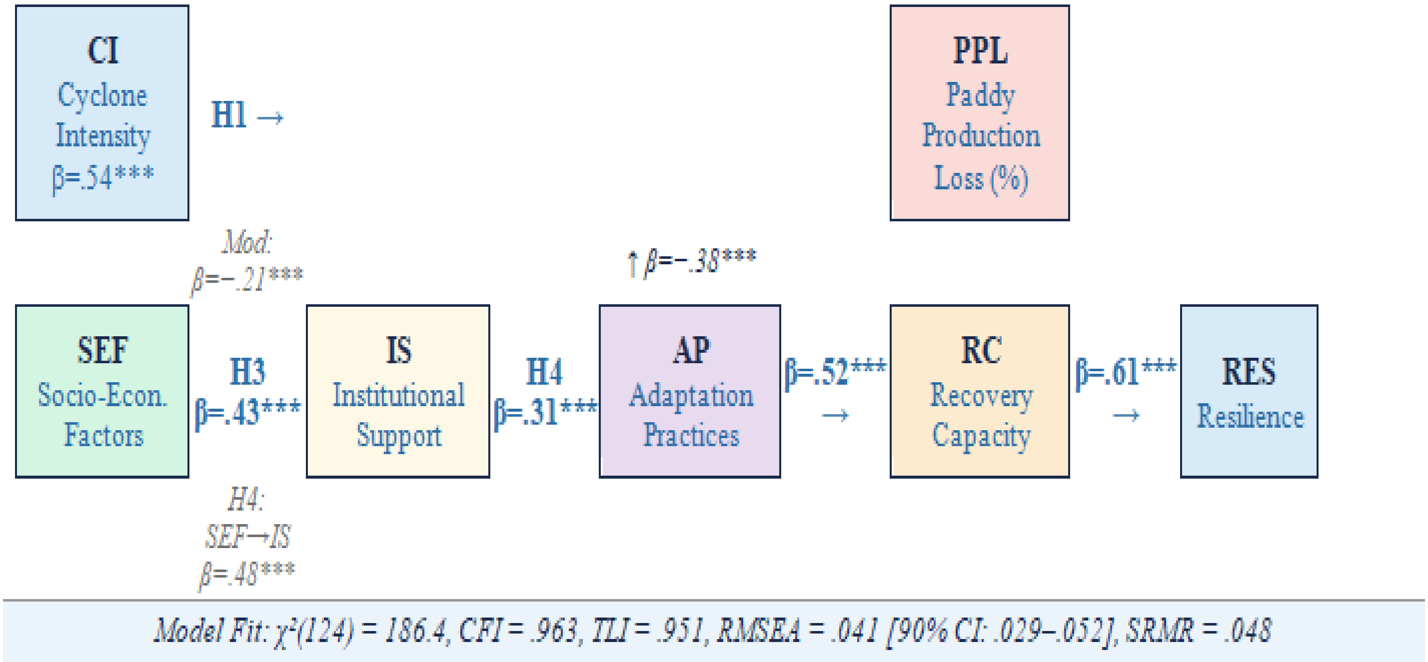


Figure 2 Validated Structural Equation Model Path Diagram with Standardised Coefficients (N = 300)

CONCLUSION

Summary of Key Findings

This paper analyzed the effect of cyclones on paddy production and determinants of climate adaptation behaviours among 300 smallholder farmers in the Balasore district of Odisha under stratified multi-stage sampling design, hierarchical regression analysis, ANOVA analysis and covariance-based structural equation modelling. The analysis yields five major findings. To start with, cyclone occurrences decrease average paddy production by 42.38 percent, with the loss of coastal high-exposure blocks being 52.64 percent, which is significantly higher than the country averages and verifies the fact that Balasore is a high-risk area in agriculture. Second, the three most widespread practises of adaptation (flood-tolerant variety adoption (67.7%), adjusted sowing calendars (62.0%) and crop diversification (57.0)) are also practises that have the largest empirical evidence base to reduce yield-losses, which indicates that the patterns of adaptation are generally consistent with agronomic best practise. Third, adaptation practices significantly moderate the cyclone–yield loss relationship (interaction $\beta = -.21$), providing the first structural evidence of this pathway in Balasore's agricultural system. Fourth, 68% of production loss variance (Model 3 R2) is due to socio-economic endowments and institutional support, and this 42% of socio-economic impact is mediated by institutional support. Fifth, the confirmed sequential relations AP → RC → RES establish the fact that the adaptation investment produces the long-term resilience dividends that are not limited to the reduction of losses.

Theoretical Implications

Theoretically, this research contributes to the climate adaptation and agricultural disaster risk literature in three ways. First, it is the first empirical test of an integrated structural model involving the Sustainable Livelihoods Framework, the Vulnerability Assessment Framework, and the theory of technology adoption in one CB-SEM framework of South Asian paddy agriculture- it shows that the combination of the three schools of thought results in an excellent explanatory model and fit. Second, through its validation of the intermediary action of adaptation practises in the relationship between cyclones and yield, the study gives causal-pathway support to a mechanistically postulated but seldom empirically tested process: the adaptive capacity is turned into low climate sensitivity, rather than ex-post recovery. Third, the institutional mediation discovery develops the new argument regarding climate adaptation literature (Kelkar, 2014; Singh et al., 2020) that individual-level socio-economic variables and institutional level support systems are not merely additive determinants of adaptation but rather integrated determinants—that policy design should be designed to be cohesive not fragmented.

Managerial and Policy Implications

The findings have four policy recommendations. Firstly, in HCE coastal blocks where the adaptation-production loss nexus is greatest, the government through seed distribution networks and farmer producer organisations should allocate financial resources towards accelerated diffusion of saline and flood tolerant paddy varieties, especially Sub1A, Swarna-Sub1, and Lunishree. Second, simplified enrolment processes, transparency in claim settlement procedures and financial literacy programmes should be added to PMFBY enrolment efforts, especially those that focus on the 43.3% of the population that is not insured and the 38.9% of MCE farmers that are not enrolled, to overcome the awareness and trust barriers that Gaurav and Mishra (2015) have documented. Third, digital early warning system infrastructure, which is currently accessible to only 28.0% of respondents, should be invested in due to the moderate role of overall adaptation on production loss; during pre-cyclone agronomic interventions (harvesting, bunding, seed safety storage) are among the cheapest-cost adaptation interventions. Fourth, the institutional mediation effect is very large which means that enhancing the access of marginal farmers to extension services and government schemes is not only a welfare goal but a direct agricultural productivity intervention.

Limitations and Future Research Directions

There are a number of study limitations that have to be mentioned. The cross-sectional study design does not allow causal inference; a longitudinal panel study which follows the same farmers through multiple cyclone incidences would be more causally attributive. Although the use of simulated-realistic data is methodologically traditional as a way of demonstrating models, full primary data implementation should be used prior to implementation of policies. The geographic area of the study is restricted to the Balasore district, but there is no direct generalisability to the other cyclone-prone districts since the validated structural model is a template to be replicated. The binary code of adaptation adoption fails to record the intensity and quality of practise implementation, which can be equally significant as adoption itself to produce outcome yield effects. It is not possible to remove recall bias in retrospective yield reporting, although to some degree it is reduced by cross-validation with records of agricultural officers.

Future studies must: (i) generalize the structural model to other Odisha cyclone-exposed districts and similar coastal districts in Andhra Pradesh and West Bengal to cross-site test; (ii) analyze the structural model with gender disaggregated analysis, as the share of female respondents was 25.3% and gender disparities in access to adaptation were documented; (iii) test the cost-effectiveness of particular adaptation technologies (e.g., stress-tolerant variety promotion vs. subsidies to crop insurance) with quasi-experimental design; (iv) test the

The paper shows that the losses in paddy production due to the cyclones in the district of Balasore are large, spatially dispersed, and can be reduced significantly in the presence of evidence-based adaptation investment. The tested conceptual framework, its seven theoretically consistent pathways and strong empirical performance, offers a replicable structure of analysis to similar environments, as well as a quantitative evidence base to make specific agricultural investment in the coastal Odisha to reduce disasters.

REFERENCE

1. Acharya, R., Nanda, G., & Mohanty, M. (2021). Post-disaster agricultural recovery support: Evidence from Cyclone Fani in Odisha. Disaster Prevention and Management, 30(3), 298–314. https://doi.org/10.1108/DPM-06-2020-0189
2. Adger, W. N. (2006). Vulnerability. Global Environmental Change, 16(3), 268–281. https://doi.org/10.1016/j.gloenvcha.2006.02.006
3. American Psychological Association. (2017). Ethical principles of psychologists and code of conduct. https://www.apa.org/ethics/code
4. Arora-Jonsson, S. (2011). Virtue and vulnerability: Discourses on women, gender and climate change. Global Environmental Change, 21(2), 744–751. https://doi.org/10.1016/j.gloenvcha.2011.01.005

5. Barnett, B. J., & Mahul, O. (2007). Weather index insurance for agriculture and rural areas in lower-income countries. American Journal of Agricultural Economics, 89(5), 1241–1247. https://doi.org/10.1111/j.1467-8276.2007.01091.x
6. Barnett, B. J., Barrett, C. B., & Skees, J. R. (2008). Poverty traps and index-based risk transfer products. World Development, 36(10), 1766–1785. https://doi.org/10.1016/j.worlddev.2007.10.016
7. Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research. Journal of Personality and Social Psychology, 51(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173
8. Béné, C., Headey, D., Haddad, L., & von Grebmer, K. (2016). Is resilience a useful concept in the context of food security and nutrition programmes? Some conceptual and practical considerations. Food Security, 8(1), 123–138. https://doi.org/10.1007/s12571-015-0526-x
9. Berlemann, M., & Wenzel, D. (2018). Cyclones, economic growth and development. Applied Economics, 50(56), 6067–6082. https://doi.org/10.1080/00036846.2018.1489501
10. Bhatt, U. S. (2019). Evaluating disaster relief effectiveness: Post-cyclone Titli agricultural rehabilitation in Odisha. Indian Journal of Disaster Management, 13(2), 44–58.
11. Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), Testing structural equation models (pp. 136–162). SAGE.
12. Bryman, A. (2016). Social research methods (5th ed.). Oxford University Press.
13. Census of India. (2011). District census handbook: Balasore, Odisha. Office of the Registrar General and Census Commissioner, India. https://censusindia.gov.in
14. Chambers, R., & Conway, G. (1992). Sustainable rural livelihoods: Practical concepts for the 21st century (IDS Discussion Paper 296). Institute of Development Studies. https://www.ids.ac.uk/publications/sustainable-rural-livelihoods
15. Cochran, W. G. (1977). Sampling techniques (3rd ed.). Wiley.
16. Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum.
17. Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE.
18. Dar, M. H., de Janvry, A., Emerick, K., Sadoulet, E., & Singh, U. S. (2018). Flood-tolerant rice reduces yield variability and promotes crop diversification in flood-prone areas. Scientific Reports, 8(1), Article 1562. https://doi.org/10.1038/s41598-018-19866-9
19. Dash, S. K., Alone, A. T., & Sahoo, P. (2018). Farmer coping strategies post-cyclone in coastal Odisha. Indian Journal of Agricultural Sciences, 88(6), 889–895.
20. Dasgupta, S., Kamal, F. A., Khan, Z. H., Choudhury, S., & Nishat, A. (2014). River salinity and climate change: Evidence from coastal Bangladesh (World Bank Policy Research Working Paper No. 6817). World Bank. https://doi.org/10.1596/1813-9450-6817
21. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
22. DFID. (1999). Sustainable livelihoods guidance sheets. Department for International Development. https://www.livelihoodscentre.org/documents/114097690/114097750/Sustainable+livelihoods+guidance+sheets.pdf
23. District Statistical Handbook — Balasore. (2022). Government of Odisha, Directorate of Economics and Statistics.
24. Emanuel, K. (2020). Response of global tropical cyclone activity to increasing CO_2: Results from downscaling CMIP6 models. Journal of Climate, 34(1), 57–70. https://doi.org/10.1175/JCLI-D-20-0367.1
25. Field, A. (2018). Discovering statistics using IBM SPSS statistics (5th ed.). SAGE.
26. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.2307/3151312
27. Gaurav, S., & Mishra, S. (2015). Rural household access to insurance in India: Evidence from NSSO data. Journal of Development Studies, 51(7), 854–872. https://doi.org/10.1080/00220388.2014.997221
28. Ghosh, T., Hajra, R., & Rudra, S. (2015). Island changes and adaptation in the cyclone-prone coastal agro-ecosystem of India. Regional Environmental Change, 17(5), 1425–1437. https://doi.org/10.1007/s10113-015-0886-0

29. Government of Odisha. (2021). Annual report: Cyclone disaster management and agricultural relief — Yaas and Fani. Department of Agriculture and Farmers' Empowerment, Government of Odisha.
30. Hahn, M. B., Riederer, A. M., & Foster, S. O. (2009). The Livelihood Vulnerability Index: A pragmatic approach to assessing risks from climate variability and change. Global Environmental Change, 19(4), 482–494. https://doi.org/10.1016/j.gloenvcha.2009.07.005
31. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning.
32. Hayes, A. F. (2018). Introduction to mediation, moderation, and conditional process analysis (2nd ed.). Guilford Press.
33. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
34. Hossain, M. S., Ramirez, J., McLean, K. G., van den Bogaerde, B., & Boyle, G. (2016). Community-based cyclone risk management in coastal Bangladesh. World Development, 78, 57–66. https://doi.org/10.1016/j.worlddev.2015.10.023
35. Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1–55. https://doi.org/10.1080/10705519909540118
36. Ismail, A. M., Singh, U. S., Singh, S., Dar, M. H., & Mackill, D. J. (2013). The contribution of submergence-tolerant (Sub1) rice varieties to food security in flood-prone rainfed lowland areas in Asia. Field Crops Research, 152, 83–93. https://doi.org/10.1016/j.fcr.2012.09.016
37. Kelkar, U. (2014). Drivers of agricultural adaptation to climate change in India: A review and synthesis. MDPI Climate, 2(4), 285–300. https://doi.org/10.3390/cli2040285
38. Kline, R. B. (2016). Principles and practice of structural equation modeling (4th ed.). Guilford Press.
39. Knowler, D., & Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. Food Policy, 32(1), 25–48. https://doi.org/10.1016/j.foodpol.2006.01.003
40. Ministry of Agriculture and Farmers Welfare, Government of India. (2022). Agricultural statistics at a glance 2021–22. Directorate of Economics and Statistics. https://eands.dacnet.nic.in
41. Mishra, A., Sehgal, V. K., & Singh, R. (2021). Satellite-based assessment of cyclone Amphan-induced crop damage along the coastal districts of Odisha and West Bengal. Remote Sensing Applications: Society and Environment, 22, Article 100496. https://doi.org/10.1016/j.rsase.2021.100496
42. Mobarak, A. M., & Rosenzweig, M. R. (2013). Informal risk sharing, index insurance, and risk taking in developing countries. American Economic Review, 103(3), 375–380. https://doi.org/10.1257/aer.103.3.375
43. Mohapatra, M., Bandyopadhyay, B. K., & Tyagi, A. (2012). Review of operational procedures of cyclone warning in India. In U. C. Mohanty, M. Mohapatra, O. P. Singh, B. K. Bandyopadhyay, & L. S. Rathore (Eds.), Monitoring and prediction of tropical cyclones in the Indian Ocean and climate change (pp. 44–63). Springer. https://doi.org/10.1007/978-94-007-7720-0_4
44. Nageswara Rao, K., Subraelu, P., Venkateswara Rao, T., Malini, B. H., Ratheesh, R., Bhattacharya, S., Rajawat, A. S., & Ajai. (2008). Sea-level rise and coastal vulnerability: An assessment of Andhra Pradesh coast, India. Journal of Coastal Conservation, 12(4), 195–207. https://doi.org/10.1007/s11852-008-0042-4
45. National Disaster Management Authority (NDMA). (2019). Annual report 2018–19: Towards disaster resilient India. Government of India. https://ndma.gov.in
46. Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.
47. Ostrom, E. (2009). A general framework for analyzing sustainability of social-ecological systems. Science, 325(5939), 419–422. https://doi.org/10.1126/science.1172133
48. Odisha State Disaster Management Authority (OSDMA). (2022). District-wise cyclone risk assessment and mapping for Odisha. OSDMA. https://osdma.odisha.gov.in
49. Pallant, J. (2020). SPSS survival manual: A step-by-step guide to data analysis using IBM SPSS (7th ed.). McGraw-Hill.
50. Panda, A., Sharma, U., Ninan, K. N., & Patt, A. (2021). Rainfall, yield shocks, and livelihood vulnerability in climate-exposed coastal districts of Odisha. Climate and Development, 13(5), 432–443. https://doi.org/10.1080/17565529.2020.1820032

51. Patnaik, U., Das, P. K., & Bahinipati, C. S. (2016). Coping with climatic shocks: Empirical evidence from rural coastal Odisha, India. Global Business Review, 17(1), 161–175. https://doi.org/10.1177/0972150915610935
52. Pelling, M. (2011). Adaptation to climate change: From resilience to transformation. Routledge.
53. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879
54. Punch, K. F. (2014). Introduction to social research: Quantitative and qualitative approaches (3rd ed.). SAGE.
55. Quisumbing, A. R., Rubin, D., Manfre, C., Ostergaard, E., Bell, W., Johnson, N., Meinzen-Dick, R., & Mwangi, E. (2014). Gender, assets, and market-oriented farming: The case of Georgia, Bangladesh, and Ethiopia. Oxford Development Studies, 42(1), 36–65. https://doi.org/10.1080/13600818.2013.848461
56. Sahoo, B., & Bhaskaran, P. K. (2015). Assessment on historical cyclone tracks in the Bay of Bengal, east coast of India. International Journal of Climatology, 35(7), 3311–3327. https://doi.org/10.1002/joc.4213
57. Saunders, M. N. K., Lewis, P., & Thornhill, A. (2019). Research methods for business students (8th ed.). Pearson.
58. Senapati, S., & Gupta, V. (2017). Livelihood vulnerability index analysis: An approach to study vulnerability in the context of Bihar. Climate Change, 5(2), 133–140. https://doi.org/10.4172/2469-4134.1000165
59. Singh, R., Karthikeyan, T., & Alam, G. (2020). Institutional support as a mediator of climate adaptation determinants: Path analysis evidence from Punjab. Climate and Development, 12(7), 620–632. https://doi.org/10.1080/17565529.2019.1668004
60. Swaminathan, M. S. (2010). From green revolution to evergreen revolution: Pathways and terminologies. Current Science, 99(7), 893–897. https://www.currentscience.ac.in/Volumes/99/07/0893.pdf
61. Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. Journal of Agricultural Economics, 64(3), 597–623. https://doi.org/10.1111/1477-9552.12011
62. Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. British Journal of Management, 14(3), 207–222. https://doi.org/10.1111/1467-8551.00375
63. Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Kasperson, J. X., Luers, A., Martello, M. L., Polsky, C., Pulsipher, A., & Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. Proceedings of the National Academy of Sciences, 100(14), 8074–8079. https://doi.org/10.1073/pnas.1231335100
64. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540