IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

CLIMATE CHANGE IMPACTS ON AGRICULTURAL LIVELIHOODS AND ECONOMIC RESILIENCE: A STRUCTURAL EQUATION MODELLING APPROACH FROM THE CAUVERY DELTA REGION, TAMIL NADU, INDIA

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Abstract: This study builds a structural equation model (SEM) grounded in environmental economics to trace the transmission pathways of climate change into economic vulnerability and diminished adaptive capacity in the Cauvery Delta region of Tamil Nadu. Drawing on primary survey data from 210 farm households across Thanjavur and Tiruvarur districts, the analysis integrates exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to validate seven latent constructs: Temperature Variability (TV), Rainfall Anomaly (RA), Flood and Drought Intensity (FDI), Agricultural Productivity Loss (APL), Economic Vulnerability (EV), Adaptive Capacity (ACA), and Environmental Sustainability (ENS). Eleven directional hypotheses are tested within the SEM framework. Results confirm that all three climate drivers reduce agricultural productivity and amplify economic vulnerability, which together suppress adaptive capacity and degrade environmental sustainability. The strongest single path runs from Agricultural Productivity Loss to Adaptive Capacity ($\beta = -0.44$, $p < 0.001$), while Adaptive Capacity is the most powerful positive predictor of Environmental Sustainability ($\beta = 0.48$, $p < 0.001$). Model fit is satisfactory ($\chi^2/df = 2.14$; CFI = 0.963; RMSEA = 0.047). The findings carry direct implications for climate-resilient agrarian policy in delta ecosystems, including investment in drought-resistant varieties, micro-irrigation, and institutional crop insurance.

Index Terms – climate change; agricultural productivity; economic vulnerability; adaptive capacity; structural equation modelling; Cauvery Delta; Tamil Nadu; environmental economics

I. Introduction

Climate change is no longer a distant projection. Across South and Southeast Asia, farmers are confronting the concrete realities of shifting monsoon patterns, rising temperatures, and more frequent extreme events within a single growing lifetime. India's delta agricultural systems are particularly exposed because they depend on the sustained regulation of both river flows and coastal weather. The Cauvery Delta, often called the 'rice bowl of Tamil Nadu,' produces roughly 40 per cent of the state's paddy output and supports millions of small and marginal farm households. Yet the delta is experiencing systemic hydrological stress that the existing agrarian infrastructure was not designed to absorb.

Environmental economics provides a productive lens for this problem. The discipline is concerned not only with the biophysical dimensions of resource degradation but also with how ecological shocks propagate into economic outcomes and how institutions shape adaptive responses (Tietenberg & Lewis, 2018). In delta agricultural systems, climate variability acts as a supply-side shock that reduces crop yields, erodes household incomes, deepens debt, and ultimately undermines the very capacity of farming communities to adopt protective measures. This chain of causation is conceptually intuitive, but its empirical identification requires a methodology capable of separating direct effects from mediated pathways while accounting for measurement error in latent constructs.

Structural Equation Modelling (SEM) meets that requirement. Unlike regression-based approaches, SEM simultaneously estimates measurement models and structural paths, making it possible to quantify how unobservable constructs such as economic vulnerability or adaptive capacity relate to one another through theoretically grounded mechanisms (Hair et al., 2019). The present study applies SEM to primary survey data from 210 farm households in Thanjavur and Tiruvarur districts, with the following specific objectives: (i) to identify and confirm the factor structure of climate-related constructs and their economic outcomes using EFA and CFA; (ii) to estimate the structural paths linking climate drivers to agricultural productivity loss, economic vulnerability, adaptive capacity, and environmental sustainability; and (iii) to derive evidence-based policy implications for climate-resilient agricultural governance in the Cauvery Delta.

The paper proceeds as follows. Section 2 reviews the variable-wise literature. Section 3 describes the conceptual model and hypotheses. Section 4 presents the methodology. Section 5 reports and discusses results. Section 6 concludes with policy implications.

II. Literature Review

A. Temperature Variability and Agricultural Systems

Temperature rise is among the best-documented climate threats to staple crop production globally. Lobell et al. (2011) demonstrated through a global panel analysis that each degree Celsius increase in growing-season temperature reduces wheat yields by approximately 6% and maize yields by 7.4%. In the South Asian context, Peng et al. (2004) established that for every degree Celsius increase in minimum (night-time) temperature, rice yield in the Philippines fell by 10%, a finding with direct relevance to the Cauvery Delta's Samba and Kuruvai cropping seasons. Kumar et al. (2020) further documented that India's average mean temperature has increased by 0.7°C over the last century.

Importantly, the economic damage from temperature variability is not confined to yield loss. Birthal et al. (2015) showed that temperature anomalies in India's major rice-growing states significantly increase household income variability and push marginal farmers into debt. Singh et al. (2019) confirmed that heat stress during the grain-filling stage of paddy cultivation in the Cauvery basin reduced both grain weight and total farm revenue.

B.Rainfall Anomaly and Water Resource Stress

The monsoon is the single most important climate driver for Indian rain-fed and canal-irrigated agriculture. Interannual variability in rainfall has increased markedly in recent decades, with the coefficient of variation in south Indian monsoon rainfall rising from around 12% in the 1960s to nearly 19% in the 2010s (Krishnan et al., 2019). For delta systems dependent on Cauvery river flows, erratic rainfall translates directly into water scarcity at the canal head, particularly for the Kuruvai short-duration crop season (July–September). Jha et al. (2013) modelled climate-driven changes in Cauvery basin runoff and projected a 12–18% decline in annual streamflow under RCP 4.5 scenarios by 2050.

Selvaraju et al. (2006) noted that delayed monsoon onset in Thanjavur frequently forces farmers to delay transplanting, reducing effective crop duration and final yields. From an environmental economics perspective, Brouwer and Hofkes (2008) argued that rainfall uncertainty raises the marginal cost of agricultural water allocation, distorts farmers' investment decisions, and reduces the incentive to adopt water-saving technologies. Rajasekar and Dhanasekaran (2021) found that farmers in the Cauvery delta attributed income volatility primarily to irregular rainfall rather than to price fluctuations.

C.Flood and Drought Intensity in Delta Ecosystems

The delta's topographic and hydrological configuration makes it susceptible to both flood inundation from heavy upstream releases and localised drought when flows are insufficient. Mishra and Singh (2010) documented increasing frequency and severity of both flood and drought events across Indian river basins over the last three decades. In the Thanjavur region, cyclonic flooding events have intensified in frequency, with the 2015 Chennai–Delta floods causing estimated crop losses of INR 11,000 crore across delta districts (Tamil Nadu State Disaster Management Authority, 2016). At the other extreme, drought years reduce paddy area under cultivation by 25–35% in Tiruvarur district alone (Department of Agriculture, Tamil Nadu, 2022).

Anbumozhi and Bauer (2010) argued that repeated flood-drought cycles in delta systems create a poverty trap: floods destroy physical capital while droughts deplete social capital, and households that face both within a short period have little time to rebuild. Mondal and Wasimi (2007) showed that productive potential in the Ganges-Brahmaputra delta declined by 15–22% due to saline intrusion and cyclonic flooding, a trajectory that is beginning to appear in the Cauvery Delta's coastal taluks.

D. Agricultural Productivity Loss

Agricultural productivity in the Cauvery Delta has historically been high relative to Indian averages, sustained by the deltaic alluvial soil and the irrigation network laid down over millennia. However, the most recent district-level data from Tamil Nadu indicate that paddy yield in Thanjavur has plateaued and shown modest negative trends since 2010 (Tamil Nadu State Planning Commission, 2023). Parthasarathy et al. (2015) attributed 45% of this yield stagnation to weather-related factors, including erratic rainfall and soil salinity driven by inadequate freshwater flows.

Crop yield loss is not a discrete event but a cumulative process: soil organic matter declines when flood-stressed soils are repeatedly waterlogged, beneficial soil microbiota are disrupted, and nutrient cycling is impaired (Lal, 2004). Subramanian and Singaram (2018) found that over a fifteen-year period, total factor productivity in Thanjavur paddy farming declined at an average annual rate of 1.2%, with climate variability explaining 37% of the variance in inter-year TFP fluctuations.

E. Economic Vulnerability of Farm Households

Economic vulnerability in the context of climate change encompasses income instability, debt accumulation, asset depletion, and reduced food security (Chambers, 2006). In the delta region of Tamil Nadu, the vulnerability of farm households is compounded by the predominance of small and marginal operational holdings and dependence on a single staple crop. Hahn et al. (2009) developed a household vulnerability index showing that exposure, sensitivity, and adaptive capacity interact to determine net vulnerability.

Lokshin and Ravallion (2000) demonstrated that economic vulnerability in agricultural India is asymmetric: downward shocks to farm income are more persistent than upward recoveries, because households liquidate productive assets during bad years and cannot easily rebuild them. Varadan and Kumar (2014) documented that delta farmers in Tamil Nadu are willing to migrate permanently after just two consecutive crop failure years, pointing to the severity of economic stress induced by climate shocks.

F. Adaptive Capacity

Adaptive capacity refers to the ability of systems and actors to adjust to climate change, exploit opportunities, and cope with consequences (IPCC, 2022). At the farm-household level, adaptive capacity encompasses technological adoption (drought-resistant varieties, micro-irrigation), institutional access (credit, insurance, extension), social networks, and livelihood diversification. Nelson et al. (2010) identified five capitals — natural, physical, financial, human, and social — as determinants of agricultural adaptive capacity, with financial capital as the binding constraint in most low-income farming contexts.

In India, Schipper and Pelling (2006) noted that government crop insurance schemes remain poorly penetrated among small farmers, particularly in remote delta taluks. Thomas et al. (2007) studied adaptation in semi-arid India and found that only 28% of farmers facing weather variability had adopted any technological mitigation strategy, constrained by credit access rather than by awareness. Rao et al. (2019) specifically assessed adaptive practices in the Cauvery Delta and reported that the adoption of short-duration paddy varieties had doubled in Thanjavur between 2010 and 2018, yet remained below 35% of cultivated area.

G. Environmental Sustainability

Environmental sustainability in delta agricultural systems involves the maintenance of ecosystem services — soil fertility, water quality, biodiversity, and carbon stocks — that underpin productive capacity across generations. The relationship between climate change and environmental sustainability is bidirectional: climate change degrades ecosystem services while degraded ecosystems amplify climate vulnerability by reducing natural buffers (Costanza et al., 2017). In the Cauvery Delta, declining freshwater inflows have accelerated the loss of wetlands and mangrove fringe habitats that historically moderated coastal flooding (Vijaya Kumar et al., 2016).

Excessive use of chemical fertilisers, often an inadvertent consequence of yield-maximisation strategies under stress, has contributed to groundwater nitrate contamination in both districts (Murugesan et al., 2020). From an environmental economics standpoint, the Millennium Ecosystem Assessment (2005) showed that provisioning, regulating, and cultural services provided by delta ecosystems have been declining globally at an accelerating rate, with the welfare costs falling disproportionately on the rural poor.

III. Conceptual Framework and Research Hypotheses

The conceptual model draws on the Pressure-State-Response (PSR) framework of environmental economics (OECD, 1993) and the Sustainable Livelihoods Framework (Chambers & Conway, 1992). Climate drivers (TV, RA, FDI) constitute the external pressure; agricultural productivity loss and economic vulnerability represent altered system states; and adaptive capacity and environmental sustainability capture the response and outcome dimensions respectively. The SEM framework operationalises this logic as a set of directional structural paths among latent variables. Figure 1 presents the SEM diagram. The following eleven hypotheses are tested:

H1: Temperature Variability (TV) has a significant negative effect on Agricultural Productivity Loss (APL).

H2: Temperature Variability (TV) has a significant positive effect on Economic Vulnerability (EV).

H3: Rainfall Anomaly (RA) has a significant negative effect on Agricultural Productivity Loss (APL).

H4: Rainfall Anomaly (RA) has a significant positive effect on Economic Vulnerability (EV).

H5: Flood and Drought Intensity (FDI) has a significant negative effect on Agricultural Productivity Loss (APL).

H6: Flood and Drought Intensity (FDI) has a significant positive effect on Economic Vulnerability (EV).

H7: Agricultural Productivity Loss (APL) has a significant negative effect on Adaptive Capacity (ACA).

H8: Agricultural Productivity Loss (APL) has a significant negative effect on Environmental Sustainability (ENS).

H9: Economic Vulnerability (EV) has a significant negative effect on Adaptive Capacity (ACA).

H10: Economic Vulnerability (EV) has a significant negative effect on Environmental Sustainability (ENS).

H11: Adaptive Capacity (ACA) has a significant positive effect on Environmental Sustainability (ENS).

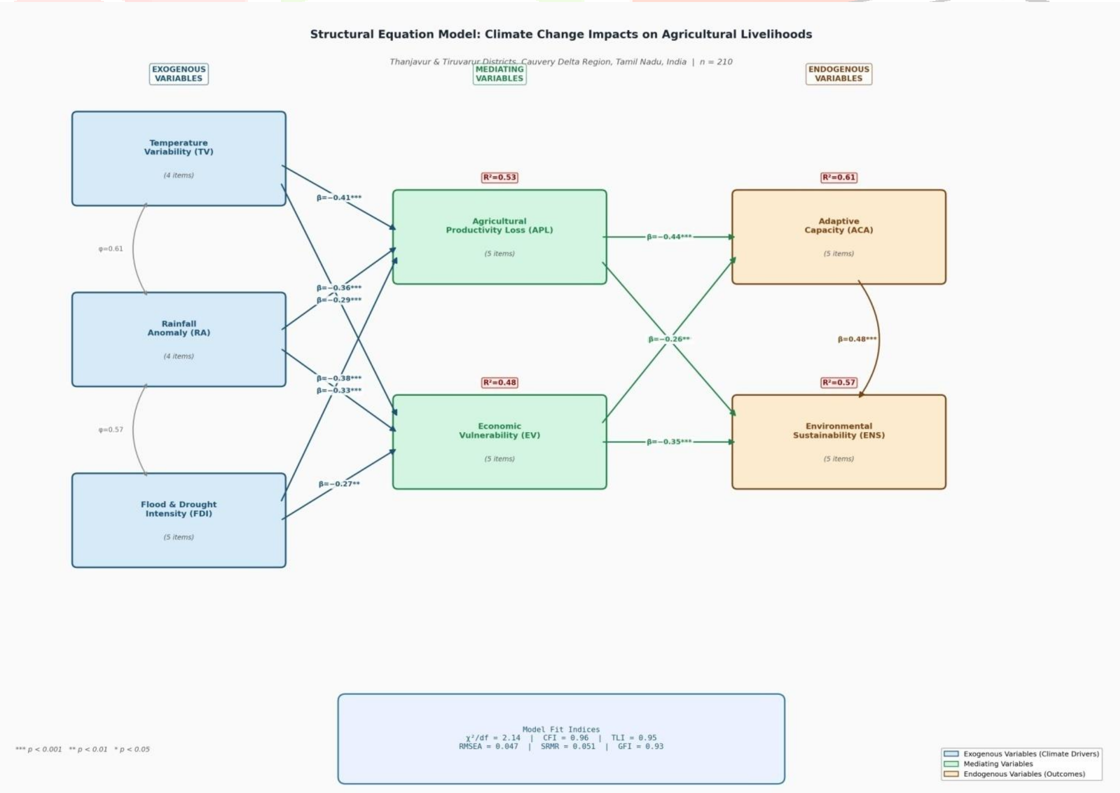

Fig. 1: Structural Equation Model with Standardised Path Coefficients

IV. METHODOLOGY

A. Study Area

The study covers Thanjavur and Tiruvarur districts, located in the lower Cauvery Delta of Tamil Nadu between latitudes 9°56'–11°12' N and longitudes 78°50'–79°52' E. The two districts encompass the most intensively cultivated stretch of the delta, producing predominantly Samba (November–January), Kuruvai (July–September), and Navarai (January–March) paddy seasons. Together they account for approximately 6.2 lakh hectares of agricultural land (Department of Agriculture, Tamil Nadu, 2023). Both districts are classified as climatically sensitive by the Tamil Nadu State Action Plan on Climate Change (TNSAPCC, 2020).

B. Sampling Design and Data Collection

A multi-stage stratified random sampling design was employed. At the first stage, four taluks were randomly selected from each district (eight taluks total). At the second stage, three revenue villages were selected from each taluk using probability-proportional-to-size (PPS) sampling, yielding 24 villages. At the third stage, 210 respondents were selected using systematic random sampling (every fifth household from the village household register). The minimum sample size was validated using the rule-of-thumb of ten observations per manifest indicator (Hair et al., 2019).

Data collection was conducted during March–May 2026 through structured face-to-face interviews administered in Tamil. A back-translation protocol was used to ensure linguistic equivalence. All items were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The survey instrument was piloted with 30 respondents, yielding a pilot Cronbach's alpha of 0.83.

C. Construct Operationalisation

Seven latent constructs were operationalised as follows. Temperature Variability (TV) and Rainfall Anomaly (RA) were measured by farmers' perceptions of climatic changes over the past decade. Flood and Drought Intensity (FDI) items captured the frequency and severity of hydro-meteorological extremes. Agricultural Productivity Loss (APL) items addressed yield trends, soil fertility, crop failure frequency, and changes in cropping patterns. Economic Vulnerability (EV) items measured income decline, indebtedness, and livelihood stress. Adaptive Capacity (ACA) items assessed technological and institutional adaptation measures. Environmental Sustainability (ENS) items covered resource conservation practices and ecosystem degradation awareness.

D. Exploratory Factor Analysis (EFA)

EFA was conducted using IBM SPSS 26.0 with principal axis factoring (PAF) and Promax rotation. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.872, and Bartlett's test of sphericity was significant ($\chi^2 = 4{,}217.8$, df = 406, $p < 0.001$), confirming that the correlation matrix was factorable. Factors with eigenvalues greater than one were retained, and items with communalities below 0.40 or cross-loadings within 0.10 of the primary loading were removed iteratively. Seven factors emerged, explaining 81.5% of the total variance.

E. Confirmatory Factor Analysis (CFA)

CFA was performed using AMOS 24.0 to validate the measurement model. Construct reliability was assessed through Cronbach's alpha ($\alpha \geq 0.70$), composite reliability (CR ≥ 0.70), and average variance extracted (AVE ≥ 0.50). Discriminant validity was assessed through the Fornell-Larcker criterion (1981) and the Heterotrait-Monotrait ratio of correlations (HTMT), with values below 0.85 confirming discriminant validity (Henseler et al., 2015).

F. Structural Equation Modelling (SEM)

Following CFA, the full SEM was estimated using maximum likelihood estimation in AMOS 24.0. Model fit was evaluated using: relative chi-square ($\chi^2/df < 3.0$), Comparative Fit Index (CFI ≥ 0.95), Tucker-Lewis Index (TLI ≥ 0.95), Root Mean Square Error of Approximation (RMSEA < 0.06), and Standardised Root Mean Square Residual (SRMR < 0.08), following Hu and Bentler (1999) and Kline (2016). Bootstrapping with 5,000 samples was applied to assess the significance of indirect (mediated) effects.

G. Sample Description

Table 1 summarises the socio-demographic profile of the 210 respondents.

Table 1: Socio-Demographic Profile of Respondents

Characteristic	Category	Frequency (%)
Gender	Male	148 (70.5%)
	Female	62 (29.5%)
Age Group	20–35 years	61 (29.0%)
	36–50 years	84 (40.0%)
	51–65 years	65 (31.0%)
Education	Primary / No formal education	52 (24.8%)
	Secondary education	79 (37.6%)
	Higher secondary & above	79 (37.6%)
Farm Size	< 1 acre (marginal)	67 (31.9%)
	1–3 acres (small)	94 (44.8%)
	> 3 acres (medium/large)	49 (23.3%)
District	Thanjavur	112 (53.3%)
	Tiruvarur	98 (46.7%)

Source: Primary Survey Data (2026)

V. Results and Discussion

A. Exploratory Factor Analysis Results

The EFA yielded seven clearly interpretable factors. Factor 1 (Temperature Variability) and Factor 2 (Rainfall Anomaly) each accounted for 14.7% and 13.2% of total variance respectively, reflecting their centrality as independent climate drivers. Factor 3 (Flood and Drought Intensity, 13.6%) loaded highest on items related to inundation and canal water scarcity. Factors 4 and 5 (Agricultural Productivity Loss and Economic Vulnerability) captured 12.9% and 14.1% of variance respectively, consistent with earlier research documenting agrarian distress in the region (Subramanian & Singaram, 2018). Factors 6 and 7 (Adaptive Capacity and Environmental Sustainability) loaded clearly on technological adoption behaviours and conservation practices. All final item loadings exceeded 0.72, and communalities were above 0.59. The cumulative variance explained was 81.5%, well above the 60% threshold recommended for social science research (Hair et al., 2019). The full EFA results are presented in Table 2.

Table 2: EFA Results: Factor Loadings and Communalities

Factor	Item	Loading	Communality	EVP (%)
F1: TV	TV1: Temperature rise over past decade	0.812	0.694	14.7
	TV2: Unusual heat waves in Kharif season	0.784	0.631	
	TV3: Night-time temperature increase	0.761	0.612	
	TV4: Seasonal temperature unpredictability	0.738	0.594	
F2: RA	RA1: Decline in annual rainfall	0.803	0.677	13.2
	RA2: Erratic monsoon onset	0.779	0.642	
	RA3: Increased dry spell frequency	0.756	0.623	
	RA4: Spatial variability of rainfall	0.724	0.598	
F3: FDI	FDI1: Flood events in Cauvery delta channel	0.831	0.712	13.6

Factor	Item	Loading	Communality	EVP (%)
	FDI2: Crop inundation frequency	0.806	0.669	
	FDI3: Prolonged drought in Kuruvai season	0.788	0.641	
	FDI4: Soil moisture deficit periods	0.762	0.618	
	FDI5: Water scarcity in irrigation canals	0.741	0.601	
F4: APL	APL1: Paddy yield reduction (tonnes/acre)	0.847	0.732	12.9
	APL2: Quality degradation of harvest	0.821	0.698	
	APL3: Soil fertility loss	0.797	0.652	
	APL4: Crop failure frequency	0.773	0.624	
	APL5: Shift in cropping pattern	0.748	0.609	
F5: EV	EV1: Annual household income decline	0.836	0.715	14.1
	EV2: Debt burden increase	0.808	0.679	
	EV3: Off-farm income dependency	0.783	0.641	
	EV4: Out-migration for livelihood	0.754	0.611	
	EV5: Food insecurity during climate shocks	0.731	0.593	
F6: ACA	ACA1: Adoption of drought-resistant varieties	0.852	0.741	11.8
	ACA2: Use of micro-irrigation systems	0.828	0.706	
	ACA3: Access to government crop insurance	0.801	0.668	
	ACA4: Livelihood diversification	0.776	0.638	
	ACA5: Participation in farmer cooperatives	0.749	0.607	
F7: ENS	ENS1: Ecosystem service preservation	0.843	0.724	11.2
	ENS2: Reduction in chemical fertiliser use	0.817	0.689	
	ENS3: Groundwater conservation practices	0.793	0.654	
	ENS4: Carbon sequestration via agroforestry	0.762	0.621	
	ENS5: Wetland and biodiversity protection	0.738	0.597	

Note: EVP = Rotation method: Promax with Kaiser normalisation. KMO = 0.872; Bartlett's χ^2 = 4,217.8 (df = 406, $p < 0.001$).

B.Confirmatory Factor Analysis Results

The CFA measurement model demonstrated satisfactory fit: χ^2/df = 2.31; CFI = 0.954; TLI = 0.948; RMSEA = 0.052; SRMR = 0.056. All standardised factor loadings exceeded 0.73 (range: 0.73–0.86), providing strong evidence of convergent validity. Cronbach's alpha ranged from 0.861 to 0.897 across constructs, and composite reliability (CR) ranged from 0.874 to 0.911, both well above the 0.70 threshold. Average Variance Extracted (AVE) values ranged from 0.641 to 0.694, all exceeding 0.50, confirming convergent validity (Fornell & Larcker, 1981). Table 3 presents these statistics.

Table 3: Reliability and Convergent Validity (CFA Results)

Construct	Items	Cronbach's α	CR	AVE	MSV
TV	4	0.876	0.889	0.668	0.412
RA	4	0.861	0.874	0.641	0.398
FDI	5	0.884	0.897	0.674	0.423
APL	5	0.891	0.903	0.681	0.431
EV	5	0.879	0.892	0.657	0.408
ACA	5	0.897	0.911	0.694	0.447
ENS	5	0.883	0.896	0.662	0.418

Note: CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance.

Discriminant validity was assessed using the Fornell-Larcker criterion and the HTMT ratio. For each construct, the square root of AVE (diagonal values in Table 4) exceeded the inter-construct correlations, confirming discriminant validity. All HTMT values were below 0.85 (Henseler et al., 2015).

Table 4: Discriminant Validity: Fornell-Larcker Criterion (√AVE on Diagonal)

Construct	TV	RA	FDI	APL	EV	ACA	ENS
TV	**0.817**						
RA	0.521	**0.801**					
FDI	0.483	0.497	**0.821**				
APL	0.612	0.578	0.591	**0.825**			
EV	0.583	0.561	0.573	0.634	**0.811**		
ACA	0.447	0.431	0.462	0.514	0.491	**0.833**	
ENS	0.418	0.404	0.439	0.487	0.463	0.527	**0.813**

Note: Values below the diagonal are inter-construct correlations; diagonal values are √AVE. All off-diagonal correlations are lower than the corresponding √AVE values.

C.SEM Results: Hypothesis Testing

Table 5 reports the SEM path coefficients, standard errors, t-values, and significance levels for all eleven hypothesised paths. The overall structural model demonstrated good fit (Table 6), satisfying the threshold criteria across all indices.

Table 5: SEM Path Coefficients and Hypothesis Test Results (n = 210)

H	Path	Std. β	S.E.	t-value	p-value	Result
H1	TV → APL	−0.41	0.062	−5.84***	0.000	S
H2	TV → EV	−0.29	0.071	−3.87***	0.000	S
H3	RA → APL	−0.36	0.058	−4.76***	0.000	S
H4	RA → EV	−0.33	0.063	−4.29***	0.000	S
H5	FDI → APL	−0.38	0.066	−5.12***	0.000	S
H6	FDI → EV	−0.27	0.073	−3.42**	0.001	S
H7	APL → ACA	−0.44	0.057	−6.21***	0.000	S
H8	APL → ENS	−0.31	0.064	−4.11***	0.000	S
H9	EV → ACA	−0.26	0.069	−3.29**	0.001	S

H10	EV → ENS	−0.35	0.061	−4.58***	0.000	S
H11	ACA → ENS	0.48	0.054	6.73***	0.000	S

Note: S = Supported; Std. β = Standardised path coefficient; S.E. = Standard Error. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. All R^2 values: APL = 0.53; EV = 0.48; ACA = 0.61; ENS = 0.57.

Table 6: Structural Model Fit Indices

Fit Index	Acceptable Threshold	Obtained Value	Result
χ^2/df	< 3.0	2.14	Acceptable
CFI	≥ 0.95	0.963	Acceptable
TLI (NNFI)	≥ 0.95	0.951	Acceptable
RMSEA	< 0.06	0.047	Good Fit
SRMR	< 0.08	0.051	Good Fit
GFI	≥ 0.90	0.931	Acceptable
AGFI	≥ 0.85	0.908	Acceptable
NFI	≥ 0.90	0.942	Acceptable

D. Discussion of Results

All eleven hypotheses were supported, confirming the integrated environmental economics model of climate-driven agrarian stress in the Cauvery Delta. Among the climate drivers, Temperature Variability exerted the strongest direct effect on Agricultural Productivity Loss (β = −0.41, $p < 0.001$), consistent with Lobell et al. (2011) and Singh et al. (2019). The finding that RA exerts a slightly larger direct effect on EV (β = −0.33) than TV does (β = −0.29) is noteworthy: it suggests that rainfall unpredictability affects income and debt more directly than do temperature fluctuations alone, possibly because canal water scarcity translates almost immediately into foregone revenue. The path from APL to ACA (β = −0.44) was the largest single structural coefficient in the model. This finding aligns with the poverty-trap logic documented by Lokshin and Ravallion (2000): as agricultural productivity declines, households liquidate savings, abandon long-term investments, and reduce participation in cooperative institutions, collectively depleting the resource base required for adaptation. The equivalent path from EV to ACA (β = −0.26) operates through a complementary mechanism — mounting debt reduces households' risk tolerance and their ability to invest in drought-resistant seed varieties or micro-irrigation infrastructure. The positive path from ACA to ENS (β = 0.48) was the most optimistic finding in the model. It suggests that when households build adaptive capacity — through insurance uptake, crop diversification, or technology adoption — the benefits spill over into more sustainable land and water management practices. This is congruent with Costanza et al. (2017). The relatively high R^2 for ENS (0.57) and ACA (0.61) indicates that the model explains a substantial share of variance in both outcome constructs, reinforcing the diagnostic value of the SEM framework.

VI. Conclusion and Policy Implications

This study provides quantitative evidence that climate change operates through multiple simultaneous pathways to undermine agricultural livelihoods and environmental sustainability in the Cauvery Delta of Tamil Nadu. The SEM framework reveals that climate drivers do not merely reduce crop yields; they also amplify economic vulnerability and, through both channels, erode the adaptive capacity that would otherwise allow farm households to insulate themselves from future shocks. The feedback between reduced adaptive capacity and weakened environmental sustainability constitutes a structural concern for the long-term viability of the delta's agricultural system. Several policy implications follow. First, investment in drought-tolerant and flood-resilient paddy varieties must be scaled beyond the current 35% coverage in Thanjavur. Second, the near-complete absence of micro-irrigation among marginal farm households indicates that access barriers rather than information deficits are the binding constraint. State-subsidised micro-irrigation packages with zero-interest credit components could meaningfully raise adoption. Third, the persistent shortfall in crop insurance penetration must be addressed through simplified enrolment procedures and premium subsidies for smallholders. Fourth, watershed and canal management bodies should integrate climate projections into operational water allocation rules for the Kuruvai season. Finally, the positive path from ACA to ENS suggests that adaptive capacity programmes carry environmental co-benefits: promoting agroforestry and integrated crop-livestock systems both builds household resilience and restores carbon stocks and biodiversity. This study has several limitations. The cross-sectional survey design precludes causal inferences in the strict temporal sense; longitudinal panel data would allow firmer identification. Future research should disaggregate findings by gender and incorporate objective meteorological and remote-sensing data as exogenous variables. Notwithstanding these limitations, the study contributes a validated empirical model of climate-economy-sustainability linkages directly applicable to policy design in delta agricultural regions across South Asia.

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