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Environmental Stress and Household Well-Being in Agriculture-Dependent Systems: A Comparative Analysis of Vulnerability Pathways in Indonesia

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ABSTRACT

Purpose – This study examines how environmental stress is associated with different psychosocial pathway configurations affecting household well-being in climate-sensitive rural systems, addressing limited attention to how stress is transmitted through resource, livelihood, health, economic, and psychological processes in agriculture-dependent households. The comparison is explicitly bounded to two context-specific sets of within-model associations and does not treat hazard regime as a statistically isolated cause of regional differences.

Design/methodology/approach – The study uses comparative survey data from 1,080 households across chronic-drought areas in East Nusa Tenggara and multi-hazard areas in Sumatera. Separate Partial Least Squares Structural Equation Modeling (PLS-SEM) models were estimated for NTT (n = 540) and Sumatera (n = 540), and theory-specified direct paths were evaluated with 5,000 bootstrap subsamples. Because the regional models contain non-equivalent constructs, indicators, paths, and Subjective Well-Being measures, the cross-context comparison is descriptive and conceptual; no formal multi-group coefficient test, measurement-equivalence claim, or cross-regional mediation test is made.

Findings/Results – In drought-prone NTT, significant direct paths form a sequential modeled chain linking perceived drought chronicity, water insecurity, food security, mental health stress, and the NTT well-being profile; the descriptive arithmetic product for the livelihood-resilience/economic-vulnerability chain is smaller within the NTT model. In Sumatera, significant direct paths form pollution-health and supply-chain-economic modeled chains whose descriptive arithmetic products are close in magnitude within that model. These values are descriptive multi-step products, not bootstrapped specific indirect

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effects, and they do not establish mediation, causal ordering, or a hazard-regime effect.
Originality/Value – The study contributes empirically grounded, context-sensitive archetypes that clarify conditions under which chronic attrition or cascading disruption may become more prominent in agriculture-dependent systems. It also demonstrates a transparent way to compare non-equivalent model architectures descriptively without treating their coefficients or well-being endpoints as directly interchangeable. The archetypes are presented as mechanism-oriented propositions for future longitudinal, measurement-invariant, and objectively validated research.

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1. Introduction

Environmental change in the Anthropocene increasingly disrupts the stability of human systems, particularly in rural areas where livelihoods remain highly dependent on climate-sensitive agriculture and livestock production (Zscheischler et al., 2020). While the biophysical dimensions of environmental change such as drought, extreme weather, and multi-hazard events are well documented (Intergovernmental Panel on Climate Change, 2022), less is understood about how these external stressors are internalized and translated into human well-being outcomes (Adger, 2010). Existing vulnerability assessments tend to prioritize macroeconomic losses or infrastructural damage, often overlooking the psychosocial processes through which individuals and households experience, interpret, and respond to environmental stress (Cunsolo & Ellis, 2018; Doherty & Clayton, 2011; Mongonia, 2022). This limitation is particularly consequential in smallholder systems, where exposure to environmental risk directly affects food security, water access, livestock productivity, and livelihood stability.

Indonesia provides a compelling empirical setting to examine these dynamics. As an archipelagic country exposed to diverse climatic and geological hazards, it encompasses contrasting vulnerability contexts within a shared national framework (Djalante et al., 2017). In East Nusa Tenggara (NTT), communities face chronic, slow-onset drought that progressively constrains agricultural production, water availability, and livestock systems. In contrast, regions in Sumatera are exposed to acute, interacting hazards including wildfires, floods, landslides, and seismic events that generate cascading disruptions across infrastructure, health systems, and market access (Atkinson & Alibašić, 2023; Purnomo et al., 2019, 2021). These contrasting contexts highlight a critical limitation in existing vulnerability frameworks, which often treat environmental stress as producing uniform outcomes rather than differentiated patterns of impact.

A growing body of literature has established the direct effects of environmental stressors on agriculture (Liu et al., 2018), infrastructure systems (Marchezini, 2015), and public health (Zhang et al., 2017). However, a key gap remains in understanding the mediating pathways through which these stressors influence human well-being. In particular, existing research often examines single hazards or sectors in isolation, limiting our ability to capture the interconnected and recursive nature of vulnerability processes. For example, water insecurity may exacerbate livelihood instability in farming and livestock systems, which in turn is associated with increased psychological stress and reduced adaptive capacity (Asiamah et al., 2025; Clayton, 2020; Lawrance et al., 2022; Nimo et al., 2025; Shao & Yu, 2023). Despite these insights, dominant frameworks such as the Pressure-and-Release (PAR) model primarily conceptualize vulnerability in external terms, with limited attention to the cognitive-affective processes that shape how stress is experienced and translated into well-being outcomes (Bradley & Reser, 2017; Düvel & García-Portela, 2024; Ojala et al., 2021).

More importantly, the literature has not sufficiently explained why different environmental stress regimes may correspond to different mechanisms of vulnerability. Slow-onset drought repeatedly constrains the same foundational resources, allowing scarcity to accumulate, deplete coping capacity, and become internalized as psychological stress. Acute and interacting hazards, by contrast, can interrupt several interdependent systems at once, producing concurrent health and economic pressures. Empirical comparative evidence on these mechanisms remains limited, and interventions designed for acute shocks may be poorly suited to prolonged scarcity, and vice versa (Doherty & Clayton, 2011; Haluza-DeLay, 2014; Heyd, 2021; McBean & Rodgers, 2010; Mongonia, 2022).

To address this limitation, this study examines two context-specific sets of associations in Indonesia: one estimated in drought-prone NTT and one estimated in multi-hazard areas of Sumatera. The settings are treated as empirically bounded cases of chronic attrition and cascading disruption, not as exhaustive categories or statistically equivalent regional models (Pescaroli & Alexander, 2018; Thomas et al., 2019). Using survey data from 1,080 households and separate PLS-SEM analyses, the study evaluates associations among perceived exposure, resource insecurity, livelihood resilience, health risks, economic vulnerability, psychological stress, and context-specific subjective well-being profiles. The comparison is limited to pathway shape, sign, and within-model magnitude; it does not attribute differences statistically to hazard type (Syaban & Appiah-Opoku, 2025).

This study makes three bounded contributions. First, it specifies theoretically plausible mechanisms and scope conditions under which chronic attrition or cascading disruption may be observed (O'Brien, 2012; Smith et al., 2022; Thoma et al., 2021; Wolf et al., 2015). Second, it applies a transparent descriptive comparison in which each context-specific PLS-SEM model is evaluated on its own terms without direct tests of non-equivalent coefficients. Third, it identifies adaptation priorities that are consistent with the observed associations and prior literature, while not presenting them as intervention effects demonstrated by this cross-sectional study (Cunsolo & Ellis, 2018; Mongonia, 2022; Watts et al., 2019; Werners et al., 2021; Woodhall-Melnik et al., 2017).

This study positions subjective well-being not merely as an outcome of environmental change, but as an integrative indicator reflecting how environmental, economic, and psychosocial processes interact within vulnerable rural systems. By examining these interactions across the two hazard contexts, the study provides a basis for developing more context-sensitive approaches to resilience-building in the Anthropocene. However, only the life-satisfaction item is common to both regional measures; optimism and meaningful activity are included in NTT, whereas safety and personal control are included in Sumatera. The endpoints are therefore interpreted as overlapping, context-specific well-being profiles rather than the same psychometric construct.

2. Literature Review & Hypothesis Development

2.1. Social-Ecological Vulnerability and Psychosocial Pathways

Vulnerability research in climate-sensitive systems has traditionally focused on biophysical exposure and economic loss, often prioritizing structural damage, crop yield reductions, and macroeconomic assessments (Adger, 2010; Cutter et al., 2008; Thomas et al., 2019). While these assessments provide critical insights into external system shocks, they frequently overlook the psychosocial processes through which environmental hazards are internalized and experienced by rural households (Berry et al., 2018; Lawrance et al., 2022). Recent social-ecological frameworks emphasize that vulnerability is not solely determined by hazard severity, but also by how stress is mediated through resource access, cognitive-affective responses, and household coping capacities (Thomas et al., 2019).

Despite growing recognition of climate-induced mental distress, such as eco-anxiety, solastalgia, and ecological grief, existing models (e.g., the Pressure-and-Release model) often conceptualize human impact as an external outcome rather than examining the internal, recursive pathways linking environmental stress to subjective well-being. Understanding how these stressors translate into well-being requires examining the mediating structures through which households navigate ecological disruptions.

2.2. Slow-Onset Hazards and Internalized Chronic Stress

Chronic, slow-onset environmental hazards, such as prolonged drought, exert progressive and cumulative pressure on agriculture-dependent livelihoods (Bahta & Myeki, 2022; Burrows et al., 2024; Liu et al., 2018). In arid and semi-arid agrarian settings, persistent moisture deficits disrupt foundational subsistence resources, leading directly to water insecurity and severe agricultural production losses (Khatun et al., 2021; Salmoral et al., 2020).

The literature suggests that water and food insecurity act as critical links between ecological degradation and psychosocial distress (Kimutai et al., 2023; Kornher & Sakketa, 2021). Rather than causing immediate structural destruction, chronic drought operates through continuous, slow-burning attrition, gradually exhausting household adaptive capacities and heightening financial vulnerability (Cunsolo & Ellis, 2018; Natarajan et al., 2022). Consequently, the psychological burden of managing daily resource scarcity, manifested as anxiety, sleep disruption, and prolonged stress, becomes a primary driver of declining subjective well-being in chronic hazard settings (Cianconi et al., 2020).

2.3. Multi-Hazard Cascades and Dispersed Systemic Disruptions

In contrast to slow-onset stress, multi-hazard environments are defined by acute, interacting events, such as earthquakes, floods, landslides, and forest fires, that trigger compound risks and cascading failures across interconnected systems (Pescaroli & Alexander, 2018;

Zscheischler et al., 2020). In these contexts, environmental shocks create simultaneous disruptions across spatial and sectoral scales (Djalante et al., 2017; Pescaroli & Alexander, 2018).

Research on compound disaster risk demonstrates that multi-hazard events frequently cause physical infrastructure damage, severing agricultural supply chains and disrupting market access (Djalante et al., 2017; Pescaroli & Alexander, 2018; Sovacool et al., 2021). Concurrently, events such as peatland fires generate transboundary air pollution, driving regional public health crises through elevated respiratory illnesses and strained local medical services (Grosvenor et al., 2024; Watts et al., 2019; Zhang et al., 2017). Under multi-hazard regimes, household well-being is not eroded through a single sequential pathway; rather, it faces a dispersed, concurrent assault operating through parallel economic shocks and physical health crises (Pescaroli & Alexander, 2018; Thomas et al., 2019; Zscheischler et al., 2020).

2.4. Differentiated Vulnerability Architectures Across Hazard Regimes

While existing studies have examined individual hazard types, such as drought impacts on agriculture or compound disaster dynamics, comparative empirical research on how contrasting hazard structures generate distinct psychosocial pathways remains limited (Pescaroli & Alexander, 2018; Thomas et al., 2019; Zscheischler et al., 2020). The literature often treats vulnerability mechanisms as uniform across contexts, leading to generalized adaptation policies that may misalign with ground-level realities (Thomas et al., 2019; Werners et al., 2021).

A comparative perspective is therefore useful when it treats the regional architectures as empirically grounded configurations rather than fixed categories (Thomas et al., 2019). Chronic attrition should be more prominent where households depend heavily on rain-fed production, water buffers and income diversification are limited, and scarcity recurs long enough to exhaust coping resources (Adger, 2010; Natarajan et al., 2022; Werners et al., 2021). Cascading disruption should be more prominent where hazards interact across infrastructure, health services, markets, and supply chains with limited redundancy (Pescaroli & Alexander, 2018; Zscheischler et al., 2020). These scope conditions identify when each configuration is theoretically plausible and make the comparison evaluable beyond a simple contrast of coefficient sizes (Thomas et al., 2019; Werners et al., 2021).

2.5. Mechanisms, Scope Conditions, and Alternative Explanations

The chronic attrition configuration links repeated exposure to the progressive depletion of household buffers. Drought constrains water and production, recurring scarcity reduces food security and livelihood resilience, and the continuing need to manage these pressures is associated with anxiety, hopelessness, and sleep disruption. Subjective well-being is therefore connected to environmental exposure through cumulative resource and psychosocial processes rather than through hazard intensity alone (Adger, 2010; Cunsolo & Ellis, 2018; Düvel & García-Portela, 2024).

The cascading disruption configuration rests on system interdependence. Where transport, markets, health services, and agricultural value chains are tightly coupled, interacting hazards can generate parallel pollution-health and supply-chain-economic routes. The configuration should be most visible when redundancy and institutional buffering are limited; stronger services, diversified incomes, or robust infrastructure may weaken or redirect these associations (Pescaroli & Alexander, 2018; Thomas et al., 2019; Zscheischler et al., 2020).

Plausible alternatives include baseline poverty, demographic composition, pre-existing distress, regional institutional capacity, and differences in risk perception or reporting. The cross-sectional models cannot eliminate these explanations or determine temporal ordering. The two configurations are therefore hypotheses about context-conditioned mechanisms that require longitudinal and multi-context validation.

3. Methodology

This study employs a comparative, cross-sectional research design to examine two context-specific configurations of psychosocial vulnerability: a chronic-attrition configuration in East Nusa Tenggara (NTT) and a cascading-disruption configuration in Sumatera. Separate PLS-SEM models were estimated within each setting (Adger, 2010; Cutter et al., 2008). The design supports examination of theory-specified associations, but it does not establish temporal ordering, causal effects, or statistically verified differences between the regional configurations.

PLS-SEM was selected because the study emphasizes theory-guided explanation of complex models with multiple latent constructs and multi-step chains, accommodates distributional departures common in field survey data, and permits assessment of measurement quality and in-sample explanatory strength (Adger, 2010; Hair, Hult, Ringle, & Sarstedt, 2021; Hair et al., 2017). The models were estimated separately because the two hazard contexts intentionally contain different predictors, intermediate constructs, indicators, and structural paths. Accordingly, the comparison concerns pathway configuration, sign, and within-model magnitude; it does not test statistical equality, measurement invariance, causal superiority, or equivalent indirect effects between regions.

3.1. Research Location, Context, and Timing

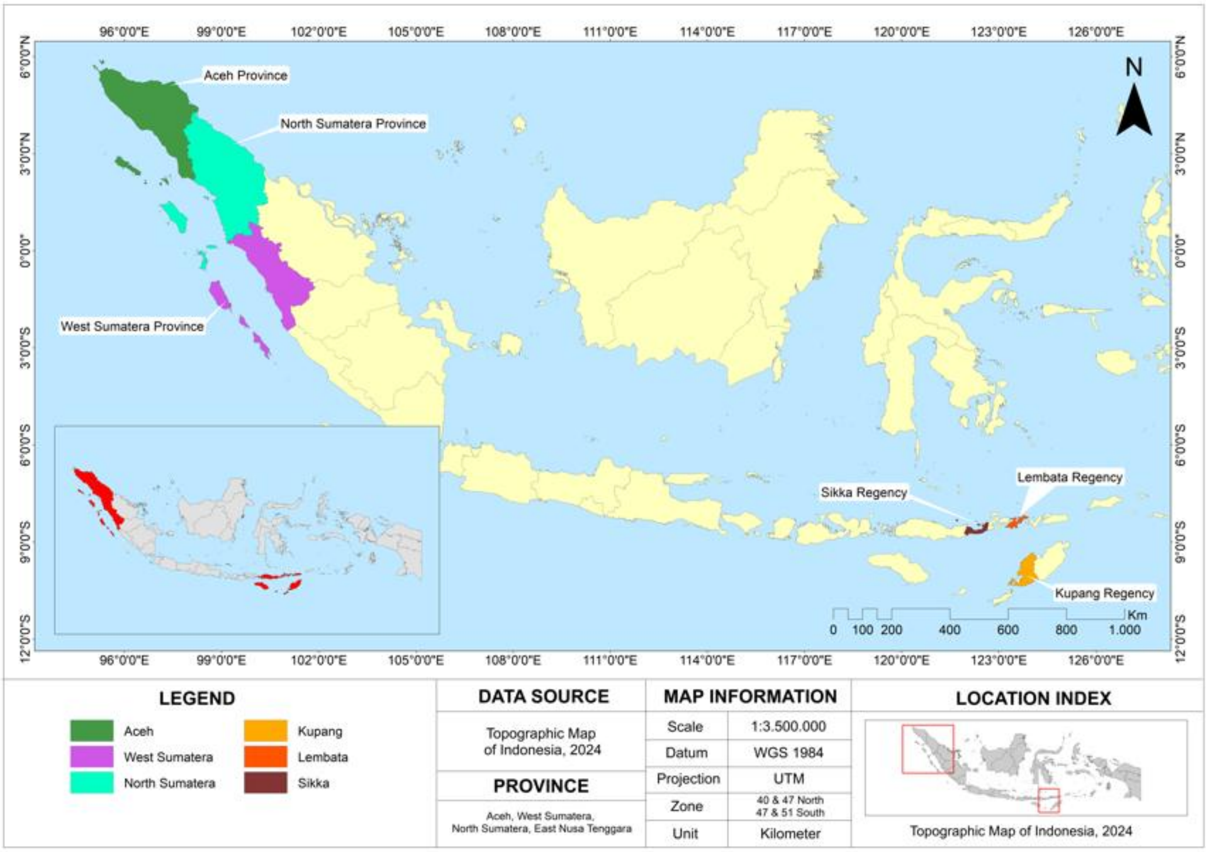
Fieldwork was conducted from May through December 2025. This eight-month window encompassed different seasonal and post-hazard conditions but was not designed or analyzed as a controlled seasonal comparison. Interview month, the site-specific fieldwork calendar, and elapsed time since the most recent relevant event were not included as covariates in the reported models. Consequently, part of the observed within-model patterns may reflect interview timing or event proximity, and no seasonal effect is inferred.

Chronic Stress Context (NTT): Research was conducted in three regencies in East Nusa Tenggara characterized by severe, recurrent drought and high agrarian dependence: Kupang (semi-arid plateaus), Sikka (rain-shadow coastal zones with fragile catchments), and Lembata (small-island ecosystems with extreme water scarcity). These areas represent a slow-onset, chronic drought context in which systemic attrition is a theoretically plausible vulnerability process.

Cascading Disruption Context (Sumatera): Research was undertaken in three provinces with documented histories of interacting multi-hazard events: Aceh (high seismic, tsunami, and flood risk), North Sumatera (transboundary haze from peatland fires and critical supply-chain nodes), and West Sumatera (earthquakes, landslides, and flash floods). These sites represent contexts in which acute, interconnected hazards may be associated with cascading disruptions across health, infrastructure, and market systems (Djalante et al., 2017; Purnomo et al., 2019, 2021).

The two cases share a broad national policy setting, but this common national context does not control for subnational differences in institutions, infrastructure, poverty, social capital, public services, or prior hazard exposure. The sites therefore provide contrasting cases for theory development rather than a natural experiment that isolates disaster typology (Hartono et al., 2024; Intergovernmental Panel on Climate Change, 2022; Purwanti et al., 2022; Rahman et al., 2021).

Figure 1. Study area map of Indonesia highlighting the two vulnerability contexts: the cascading disruption context (Sumatera: Aceh, North Sumatera, and West Sumatera provinces) and the chronic stress context (East Nusa Tenggara: Kupang, Sikka, and Lembata regencies).



3.2. Population, Sampling Strategy, and Statistical Power

The target population was household heads or their spouses in rural and peri-urban communities within the selected high-risk subnational regions. The sites were purposively selected to provide contrasting hazard contexts. The retained study documentation describes household recruitment within the selected sites as multistage stratified random sampling. Because complete sampling-flow records are unavailable, the achieved samples are treated as regional analytic samples only and are not claimed to be probability-representative of all households in NTT or Sumatera.

The stated procedure comprised three stages: (1) districts (kecamatan) within each target regency or province were stratified as High or Very High exposure using the Indonesian Disaster Risk Index (Indeks Risiko Bencana Indonesia); (2) two villages (desa) were randomly selected from each stratum; and (3) 30 households per village were selected systematically from official village household registries. The retained records do not identify the selected districts and villages or the site-level numbers approached, ineligible, refusing, replaced, and retained, and the documented stage counts do not independently reconstruct the final n = 540 per region. Therefore, response rates and replacement procedures cannot be calculated or verified, and no unrecorded sampling counts are reconstructed in this revision.

The target sample was 1,080 households, and the final analytic sample comprised 1,080 valid responses (NTT = 540; Sumatera = 540). The original sample-planning statement reported that the total sample exceeded the PLS-SEM 10-times rule and that an a priori analysis in G*Power 3.1 indicated >99% power to detect a medium effect size ($f^2 = 0.15$) at $\alpha = 0.05$, above the commonly cited 80% threshold. These original planning details are retained for transparency, but they are not used as the primary model-specific justification: the two regional models were estimated separately, so the relevant analytic sample is n = 540 per model rather than the combined N = 1,080. The retained record does not provide the complete G*Power test family, number-of-predictors setting, or output file required to reproduce a model-specific calculation, and no new power estimate is generated here. The small NTT Economic Vulnerability → Subjective Well-Being coefficient ($\beta = -0.089$) is therefore interpreted cautiously rather than treated as adequately powered merely because it is statistically significant.

3.3. Measurement

All constructs were estimated as reflective latent variables measured on a 5-point Likert scale (1 = Strongly Disagree/Very Low to 5 = Strongly Agree/Very High). Indicators were adapted from established literature and reviewed for contextual relevance. The questionnaire was developed in English, translated into Bahasa Indonesia, and back-translated to check conceptual consistency. A pilot test with 60 households, excluded from the main sample, assessed clarity, comprehensibility, and reliability. The reflective estimation is retained to report the analysis actually conducted, while the construct-specification audit below limits the interpretation of high loadings and reliability for composite-like domains.

Construct-specification audit. Perceived Drought Chronicity combines duration, soil-moisture severity, and frequency; Perceived Multi-Hazard Synergy combines co-occurrence and perceived amplification; Health Crisis spans household illness, service overload, and perceived disease vulnerability; and the Sumatera Economic Vulnerability construct combines livelihood interruption, community recovery, and adequacy of assistance. These components are not fully interchangeable manifestations, particularly ES3, which concerns institutional response. The high loadings and reliability coefficients are therefore interpreted as coherence under the reported reflective specification, not as proof that these broad domains are unidimensional or comprehensively measured. Future validation should compare narrower reflective constructs with formative or multidimensional specifications.

Scoring direction was harmonized before model estimation. WI1 was reverse-coded so higher Water Insecurity scores indicate greater insecurity. LF1 and LF3 were reverse-coded, while

LF2 retained its direction; the resulting construct is labelled Livelihood Resilience, with higher scores indicating greater diversification and recovery capacity. FS1 and FS2 were reverse-coded so higher Food Security scores indicate greater security. Higher EV, MH, MHS, TBP, SCD, HC, and ES values indicate greater vulnerability or disruption, whereas higher SWB indicates better well-being. The original LF item labels are retained in the tables solely to preserve traceability to the dataset.

The NTT model includes Perceived Drought Chronicity (DC), Water Insecurity (WI), Livelihood Resilience (LR; the original item labels LF1-LF3 are retained for traceability), Food Security (FS), Economic Vulnerability (EV), Mental Health Stress (MH), and an NTT Subjective Well-Being profile (SWB). The Sumatera model includes Perceived Multi-Hazard Synergy (MHS), Perceived Trans-Boundary Pollution (TBP), Supply Chain Disruption (SCD), Health Crisis (HC), Economic Vulnerability (ES), and a Sumatera Subjective Well-Being profile (SWB). The ES code is retained to preserve correspondence with the dataset and figures. Tables 1 and 2 present the indicators and their sources. The constructs remain deliberately context-specific; only their broader functional roles and observed pathway configurations are compared.

Cross-context measurement boundary. Only SWB1 (overall life satisfaction) is common to both regional measures. NTT SWB additionally contains optimism and meaningful daily activity, whereas Sumatera SWB contains perceived safety and personal control. The two constructs overlap but are not psychometrically equivalent; all endpoint interpretations and R-square values remain within model and are not compared as measurements of the same latent outcome.

The two hypothesized architectures are presented visually to clarify the tested paths. Figure 2 shows the Context-Sensitive Chronic Attrition Configuration for NTT. Perceived Drought Chronicity is associated with two sequential routes: one through Livelihood Resilience and Economic Vulnerability, and another through Water Insecurity, Food Security, and Mental Health Stress, both terminating in the NTT Subjective Well-Being profile.

Figure 2. Conceptual Architecture of the Context-Sensitive Chronic Attrition Configuration in East Nusa Tenggara, Indonesia

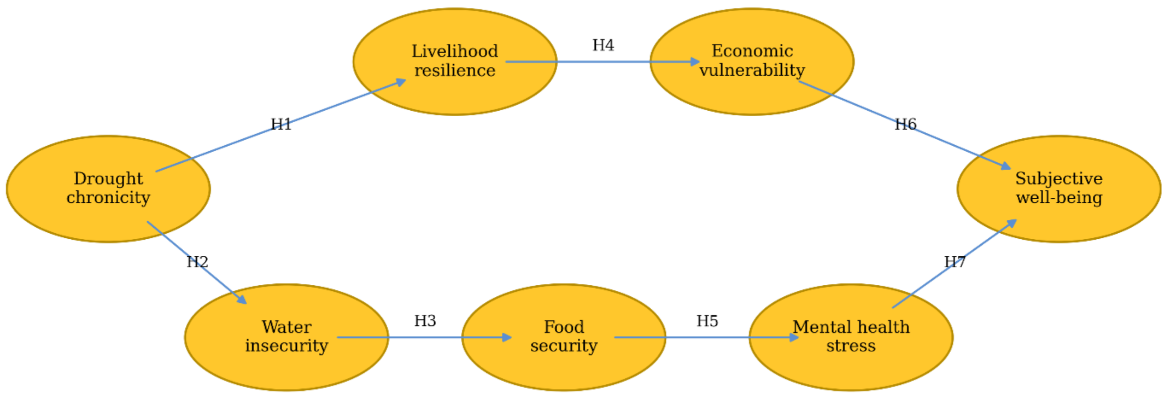
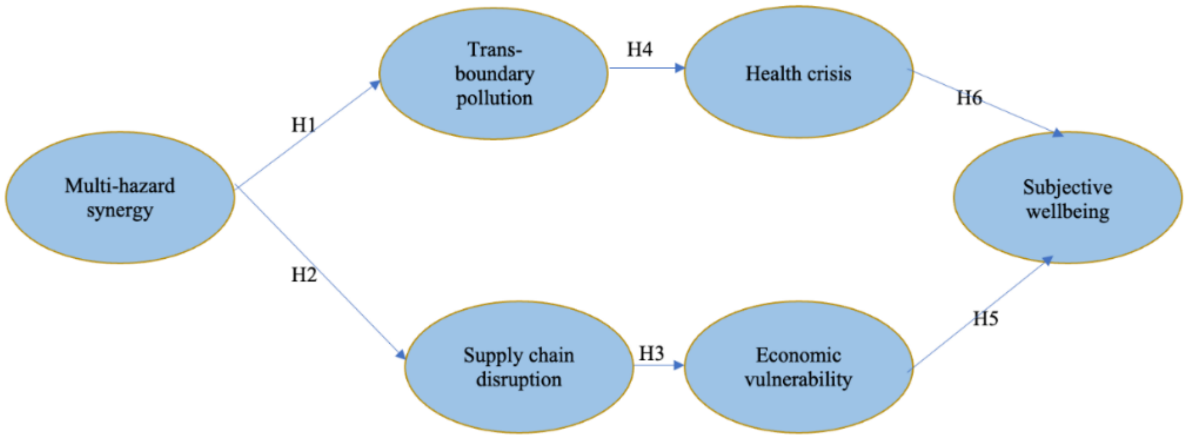


Figure 3 shows the Context-Sensitive Cascading Disruption Configuration for Sumatera. Perceived Multi-Hazard Synergy is associated with two parallel routes, through Perceived Trans-Boundary Pollution and Health Crisis and through Supply Chain Disruption and

Economic Vulnerability, before both routes connect with the Sumatera Subjective Well-Being profile.

Figure 3. Conceptual Architecture of the Context-Sensitive Cascading Disruption Configuration in Sumatera, Indonesia



Note: The figures retain the abbreviated construct labels used in the original SmartPLS models. DC, MHS, and TBP are interpreted throughout as perceived measures, and the ES code denotes the Sumatera Economic Vulnerability construct.

Tables 1 and 2 provide the detailed operational definitions. Self-reported measures remain appropriate for perceived insecurity, stress, and well-being, but they may be affected by recall, mood, and social-desirability processes. Community hazard histories were reported to have been cross-checked with local disaster-agency records where possible (Lorem et al., 2020; Reid et al., 2018; Tsai et al., 2020). However, the retained record does not identify the agencies, sites, periods, or matching procedure, and no respondent-level linkage to drought indices, rainfall anomalies, fire hotspots, PM2.5, event records, road disruptions, or health-service data was included in the models. The exposure constructs are therefore described consistently as Perceived Drought Chronicity, Perceived Multi-Hazard Synergy, and Perceived Trans-Boundary Pollution; the reported cross-check should be treated as contextual rather than individual-level validation.

Table 1. Operational Definition of Variables and Indicators

Variable	Code	Indicator	Reference
Perceived Drought Chronicity	DC1	Over the past 5 years, the duration of annual dry spells has been exceptionally long	(Liu et al., 2018)
	DC2	The severity of soil moisture deficit during drought periods is extreme	(Zscheischler et al., 2020)
	DC3	Drought events have become more frequent and predictable in the last decade	(Bahta & Myeki, 2022)
Water Insecurity	WI1 (R)	My household has reliable access to sufficient clean water for all daily needs year-round	(Khatun et al., 2021; Martin et al., 2021; Salmoral et al., 2020; Valenzuela-Mahecha et al., 2022)

Variable	Code	Indicator	Reference
	WI2	The time and financial cost of obtaining water significantly burdens my household	(Kajikawa, 2008)
	WI3	I feel anxious about the future availability of water for my family	(Doherty & Clayton, 2011; Mongonia, 2022)
Livelihood Resilience	LF1 (R)	My primary income source (e.g., farming) is highly sensitive to variations in rainfall and temperature	(Adger, 2010)
	LF2	I have diverse and stable alternative sources of income to cope with crop/livestock failure	(Natarajan et al., 2022)
	LF3 (R)	My ability to recover from a bad harvest is very low	(Nef et al., 2023)
Food Security	FS1 (R)	In the last 12 months, my household has worried about running out of food before obtaining money to buy more	(Rahman et al., 2022; Shiva & Bedi, 2002)
	FS2 (R)	The nutritional quality and diversity of my family's diet have declined due to environmental conditions	(Watts et al., 2019)
Economic Vulnerability	EV1	An unexpected expense equal to one month's income would be impossible to cover without selling assets or taking high-interest loans	(Anbumozhi et al., 2020; World Bank, 2016)
	EV2	My household debt level has increased significantly due to climate-related stresses	(World Bank, 2016)
Mental Health Stress	MH1	I have felt nervous, anxious, or on edge about environmental and livelihood problems over the last month	(Cunsolo & Ellis, 2018; Thoma et al., 2021)
	MH2	I feel a sense of hopelessness about the future due to persistent drought	(Cunsolo & Ellis, 2018)
	MH3	Problems related to water and food interfere with my sleep	(Kornher & Sakketa, 2021)
Subjective Well-Being	SWB1	All things considered, I am satisfied with my life as a whole these days	(Yang & Zou, 2025)
	SWB2	I am optimistic about my future	(Rahman et al., 2023)
	SWB3	I often feel that my daily activities are meaningful and worthwhile	(Rahman et al., 2023)

Note: (R) indicates an item reverse-coded before construct-score calculation. Higher WI indicates greater water insecurity; higher LR indicates greater livelihood resilience; higher FS indicates greater food security.

Table 2. Operational Definition of Variables and Indicators

Variable	Code	Indicator	Reference
Perceived Multi-Hazard Synergy	MHS1	Hazards in my region (fire, landslide, flood) tend to occur in rapid succession or simultaneously, amplifying damage	(Zscheischler et al., 2020)
	MHS2	The compound impact of multiple hazards is greater than the sum of their individual impacts	(Intergovernmental Panel on Climate Change, 2022)
Perceived Trans-Boundary Pollution	TBP1	Haze and air pollution from forest/peatland fires severely affect my health and daily activities for months each year	(Purnomo et al., 2019, 2021)

Variable	Code	Indicator	Reference
	TBP2	I believe the origin of major pollution events is often outside my local district/province	(Zhang et al., 2017)
Supply Chain Disruption	SCD1	Disasters frequently disrupt the transport of goods, causing shortages and price spikes for basic necessities	(Sovacool et al., 2021)
	SCD2	My access to markets to sell produce/buy supplies is highly unreliable due to damaged infrastructure (roads/bridges)	(Djalante et al., 2017)
Health Crisis	HC1	My household has experienced respiratory illness (e.g., ISPA) directly attributed to haze/air pollution in the past year	(Watts et al., 2019)
	HC2	Local health services are overwhelmed and undersupplied following major hazard events	(Axelrod, 1994; Yuan et al., 2022)
	HC3	I feel highly vulnerable to disease due to the combined stress of pollution, displacement, and poor sanitation after disasters	(Lawrance et al., 2022; Zhang et al., 2017)
Economic Vulnerability	ES1	My primary livelihood was severely interrupted or destroyed by a recent multi-hazard disaster	(Nguyen et al., 2023)
	ES2	The economic recovery of my community after a major disaster is very slow and incomplete	(Hallegatte, 2016)
	ES3	Government or NGO assistance following a disaster is insufficient and poorly targeted to meet our needs	(Nguyen et al., 2023; Ojala et al., 2021)
Subjective Well-Being	SWB1	All things considered, I am satisfied with my life as a whole these days	(Yang & Zou, 2025)
	SWB2	I feel safe and secure in my daily life and environment	(Rahman et al., 2023)
	SWB3	I have a strong sense of control over the things that happen in my life	(Rahman et al., 2023)

3.4. Data Collection Procedure

Quantitative data collection was performed by trained enumerators who were native to the respective regions to support cultural and linguistic sensitivity. Before each structured interview, enumerators obtained informed verbal consent after explaining the study purpose, anonymity guarantees, voluntary participation, and the right to withdraw. Interviews were conducted in private settings and lasted approximately 30-40 minutes. To support data quality, 20% of interviews in each region were randomly selected for a short supervisory follow-up telephone call to verify key responses. All data were anonymized at the point of entry into KoBoToolbox.

Participants provided informed verbal consent under the procedures described above. An institutional ethics committee name, approval number, or formal exemption was not available in the study records used for manuscript preparation. Accordingly, the manuscript reports the documented consent procedures but does not claim formal ethics approval or provide an unverified approval identifier.

3.5. Data Analysis Strategy

Data analysis followed three stages using SmartPLS 4 (Henseler et al., 2015). (1) Measurement-model assessment was performed separately for each regional model. Internal consistency was assessed with Cronbach's alpha and composite reliability (CR), and convergent validity with indicator loadings and average variance extracted (AVE). The original analysis procedure also specified the Fornell-Larcker criterion and HTMT for discriminant validity (Fornell & Larcker, 1981; Hair, Hult, Ringle, Sarstedt, et al., 2021; Hair et al., 2013; Henseler et al., 2016; Sarstedt et al., 2023). However, the complete numerical Fornell-Larcker and HTMT matrices and HTMT bootstrap confidence intervals are not retained in the available analytical output. Discriminant validity is therefore not claimed to be conclusively established. Because several constructs use two indicators and some reliability coefficients are very high, reliability is interpreted together with indicator content rather than as evidence of broad construct coverage.

(2) Structural-model assessment: collinearity was assessed with VIF, and theory-specified direct path coefficients were evaluated with 5,000 bootstrap subsamples. R-square was used to describe in-sample explanatory power. The available bootstrap output reports direct paths but not specific indirect-effect standard errors, p-values, or confidence intervals. Accordingly, the multi-step products reported later are descriptive arithmetic summaries rather than bootstrapped mediation tests. No out-of-sample predictive claim is made because PLSpredict results are unavailable (Hair et al., 2017; Hair, Sarstedt, Pieper, & Ringle, 2012; Shmueli et al., 2016).

(3) Cross-context comparative pattern analysis: after estimating each regional model independently, the analysis compared pathway shape, sign, and within-model point estimates. Formal multi-group coefficient tests, measurement-invariance claims, and statistical comparisons of indirect effects were not used because the models contain different constructs, indicators, paths, and non-equivalent well-being endpoints. The comparison supports a bounded description of two observed configurations, not an inference that hazard regime explains their differences.

4. Result and Discussion

4.1. Sample Profile and Descriptive Statistics

The final analytic sample contained 1,080 respondents, with 540 households in each regional model. In NTT, respondents were predominantly in the 41-50-year cluster, 70% were male, 38.9% had primary education, and 38.9% reported 15-19 years of farming experience. In Sumatera, the largest age category was 31-40 years, 64.8% were male, 33.3% had primary education, and 27.8% had junior-level education. Tables 3 and 4 provide the complete profiles. These figures characterize the achieved samples but do not establish regional representativeness or demographic equivalence; differences in age, gender, education, household size, and farming experience remain plausible alternative explanations for differences in the modeled configurations (Cutter et al., 2008; Siagian et al., 2014).

Table 3. Respondent Profile (n=540 NTT)

Description	Respondent Profile	Number	Percentage
Farmer Age	21–30 years	50	9.3
	31–40 years	120	22.2
	41–50 years	170	31.5
	51–60 years	135	25

	>60 years	65	12
Gender	Male	378	70
	Female	162	30
Family Size	<5 people	110	20.4
	5–10 people	330	61.1
	>10 people	100	18.5
Experience	10–14 years	150	27.8
	15–19 years	210	38.9
	>20 years	180	33.3
Formal Education	No education	35	6.5
	Primary education	210	38.9
	Junior education	145	26.9
	Senior education	120	22.2
	Graduate	25	4.6
	Postgraduate	5	0.9

Table 4. Respondent Profile (n=540 Sumatera)

Description	Respondent Profile	Number	Percentage
Farmer Age	21–30 years	80	14.8
	31–40 years	150	27.8
	41–50 years	155	28.7
	51–60 years	105	19.4
	>60 years	50	9.3
Gender	Male	350	64.8
	Female	190	35.2
Family Size	<5 people	150	27.8
	5–10 people	310	57.4
	>10 people	80	14.8
Experience	10–14 years	220	40.7
	15–19 years	190	35.2
	>20 years	130	24.1
Formal Education	No education	20	3.7
	Primary education	180	33.3
	Junior education	150	27.8
	Senior education	130	24.1
	Graduate	45	8.3
	Postgraduate	15	2.8

4.2. Assessment of the Measurement Model

Before structural analysis, the reported reflective specifications were assessed using the measurement information that remains available. As shown in Tables 5 and 6, Cronbach's alpha and CR exceed 0.70, indicating adequate internal consistency, although very high values, particularly for two-indicator constructs, may reflect item redundancy rather than superior measurement quality (Henseler et al., 2016). Indicator loadings exceed 0.70 and AVE exceeds 0.50, supporting convergent validity under the reported specifications (Hair et al., 2012; Sarstedt et al., 2023). Complete numerical Fornell-Larcker and HTMT matrices and HTMT bootstrap confidence intervals are not available for reporting or independent inspection. Accordingly, discriminant validity remains insufficiently documented and is not treated as conclusively demonstrated.

Food Security, Economic Vulnerability, Perceived Multi-Hazard Synergy, Perceived Trans-Boundary Pollution, and Supply Chain Disruption use only two indicators, so high reliability may partly reflect item similarity and narrow coverage. Content overlap also warrants caution: WI3 introduces anxiety into Water Insecurity while Mental Health Stress separately measures anxiety and hopelessness; Health Crisis combines illness, service-system strain, and perceived disease vulnerability; and ES3 addresses external assistance rather than household economic disruption. The reported coefficients are retained, but measurement quality is not inferred from high loadings alone.

Table 5. Outer Model Testing - NTT

Variable	Item	Loading	CA	CR	AVE
Perceived Drought Chronicity	DC1	0.938	0.931	0.955	0.877
Perceived Drought Chronicity	DC2	0.943	0.931	0.955	0.877
Perceived Drought Chronicity	DC3	0.929	0.931	0.955	0.877
Water Insecurity	WI1	0.955	0.938	0.959	0.887
Water Insecurity	WI2	0.935	0.938	0.959	0.887
Water Insecurity	WI3	0.936	0.938	0.959	0.887
Livelihood Resilience	LF1	0.91	0.906	0.941	0.842
Livelihood Resilience	LF2	0.919	0.906	0.941	0.842
Livelihood Resilience	LF3	0.924	0.906	0.941	0.842
Food Security	FS1	0.976	0.939	0.97	0.942
Food Security	FS2	0.964	0.939	0.97	0.942
Economic Vulnerability	EV1	0.921	0.912	0.952	0.909
Economic Vulnerability	EV2	0.984	0.912	0.952	0.909
Mental Health Stress	MH1	0.95	0.943	0.963	0.897
Mental Health Stress	MH2	0.945	0.943	0.963	0.897
Mental Health Stress	MH3	0.946	0.943	0.963	0.897
Subjective Well-Being	SWB1	0.96	0.953	0.97	0.915
Subjective Well-Being	SWB2	0.953	0.953	0.97	0.915
Subjective Well-Being	SWB3	0.956	0.953	0.97	0.915

Table 6. Outer Model Testing - Sumatera

Variable	Item	Loading	CA	CR	AVE
Economic Vulnerability	ES1	0.876	0.919	0.919	0.791
Economic Vulnerability	ES2	0.904	0.919	0.919	0.791
Economic Vulnerability	ES3	0.888	0.919	0.919	0.791
Health Crisis	HC1	0.924	0.924	0.924	0.802

Health Crisis	HC2	0.890	0.924	0.924	0.802
Health Crisis	HC3	0.872	0.924	0.924	0.802
Perceived Multi-Hazard Synergy	MHS1	0.930	0.923	0.923	0.856
Perceived Multi-Hazard Synergy	MHS2	0.920	0.923	0.923	0.856
Supply Chain Disruption	SCD1	0.918	0.923	0.923	0.858
Supply Chain Disruption	SCD2	0.934	0.923	0.923	0.858
Perceived Trans-Boundary Pollution	TBP1	0.932	0.929	0.929	0.867
Perceived Trans-Boundary Pollution	TBP2	0.931	0.929	0.929	0.867
Subjective Well-Being	SWB1	0.914	0.892	0.933	0.822
Subjective Well-Being	SWB2	0.903	0.892	0.933	0.822
Subjective Well-Being	SWB3	0.904	0.892	0.933	0.822

4.3. Assessment of the Structural Model and In-Sample Explanatory Power

After examining the reported measurement statistics, the structural models were evaluated. Tables 7 and 8 present the fitted-model indices. The saturated-model SRMR values were 0.016 for NTT and 0.022 for Sumatera, both below the 0.08 guideline, while the estimated-model NFI values were 0.890 for NTT and 0.974 for Sumatera. Under the reported criteria, these values support an acceptable descriptive fit of the specified models (Henseler et al., 2016; Hu & Bentler, 1999). They do not compensate for incomplete discriminant-validity reporting, establish causal fit, or demonstrate out-of-sample predictive performance.

Table 7. Model Fit Testing - NTT

Index	Saturated Model	Estimated Model
SRMR	0.016026	0.06306
d_ULS	0.048798	13.1481
d_G	0.115763	0.612673
Chi-Square	367.4359	1269.643
NFI	0.968174	0.89003

Table 8. Model Fit Testing - Sumatera

Index	Saturated Model	Estimated Model
SRMR	0.022178	0.057216
d_ULS	0.059025	0.392839
d_G	0.058268	0.046239
Chi-Square	183.2997	131.8329
NFI	0.96424	0.97428

Tables 9 and 10 show that the modeled predictors account for 65.7% of the variance in the NTT Subjective Well-Being profile and 49.7% in the Sumatera profile. These R-square values describe in-sample explanatory performance within non-equivalent endpoint measures and must not be compared as if they referred to the same latent outcome. They also do not establish out-of-sample prediction without PLSpredict assessment.

Table 9. R Square - NTT

Variable	R Square	R Square Adjusted
Mental Health Stress	0.262096	0.260724
Economic Vulnerability	0.120229	0.118593
Food Security	0.451865	0.450846
Livelihood Resilience	0.129995	0.128377
Subjective Well-Being	0.657022	0.655744
Water Insecurity	0.774294	0.773875

Table 10. R Square - Sumatera

Variable	R Square	R Square Adjusted
Economic Vulnerability	0.342928	0.341707
Health Crisis	0.408382	0.407282
Subjective Well-Being	0.497442	0.49557
Supply Chain Disruption	0.264231	0.262863
Trans-Boundary Pollution	0.328277	0.327029

All reported inner-model VIF values were below 5, with a maximum of 2.87, indicating no critical structural collinearity under that criterion (Hair et al., 2012). VIF is interpreted only as a collinearity diagnostic and not as evidence that common-method variance is absent.

4.4. Hypothesis Testing and Path Analysis

The results of the bootstrapping procedure (5,000 subsamples) for testing the hypothesized relationships are presented in Table 11 (NTT) and Table 12 (Sumatera), with the empirical models visualized in Figure 4 (NTT) and Figure 5 (Sumatera).

Table 11. Hypothesis Testing - NTT

Hyp.	Construct	O	M	STDEV	T-Statistics	p
H1	Perceived Drought Chronicity → Livelihood Resilience	-0.361	-0.367	0.037	9.646	<0.001
H2	Perceived Drought Chronicity → Water Insecurity	0.880	0.880	0.010	90.636	<0.001
H3	Water Insecurity → Food Security	-0.672	-0.672	0.044	15.43	<0.001
H4	Livelihood Resilience → Economic Vulnerability	-0.347	-0.352	0.039	8.823	<0.001
H5	Food Security → Mental Health Stress	-0.512	-0.513	0.033	15.634	<0.001
H6	Economic Vulnerability → Subjective Well-Being	-0.089	-0.089	0.034	2.597	0.009
H7	Mental Health Stress → Subjective Well-Being	-0.752	-0.751	0.029	26.35	<0.001

Table 12. Hypothesis Testing - Sumatera

Hyp.	Construct	**O**	**M**	**STDEV**	**T-Statistics**	***p***
H1	Perceived Multi-Hazard Synergy → Trans-Boundary Pollution	0.573	0.574	0.028	20.389	<0.001
H2	Perceived Multi-Hazard Synergy → Supply Chain Disruption	0.514	0.515	0.033	15.768	<0.001

Hyp.	Construct	O	M	STDEV	T-Statistics	p
H3	Supply Chain Disruption → Economic Vulnerability	0.586	0.587	0.026	22.171	<0.001
H4	Perceived Trans-Boundary Pollution → Health Crisis	0.639	0.641	0.025	25.323	<0.001
H5	Economic Vulnerability → Subjective Well-Being	-0.464	-0.464	0.027	16.957	<0.001
H6	Health Crisis → Subjective Well-Being	-0.434	-0.434	0.03	14.608	<0.001

Figure 4. Empirical Structural Model – NTT (Livelihood Resilience Scoring Clarified)

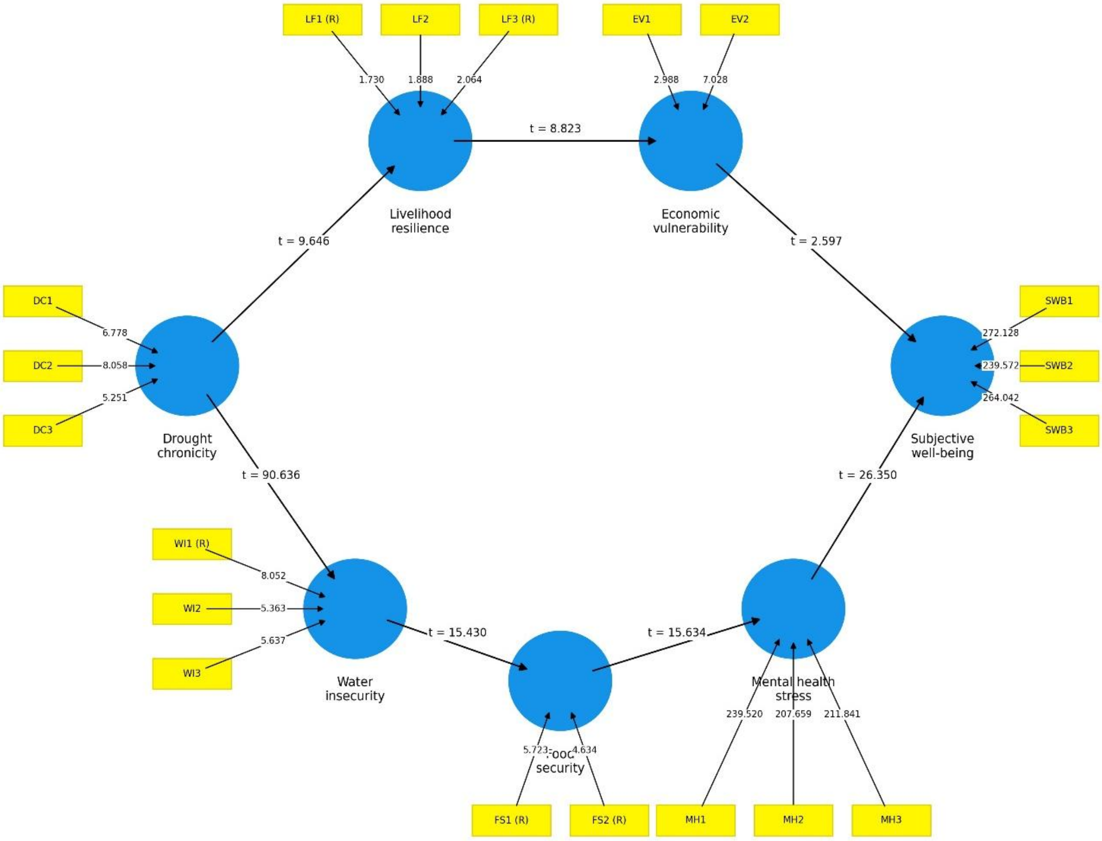
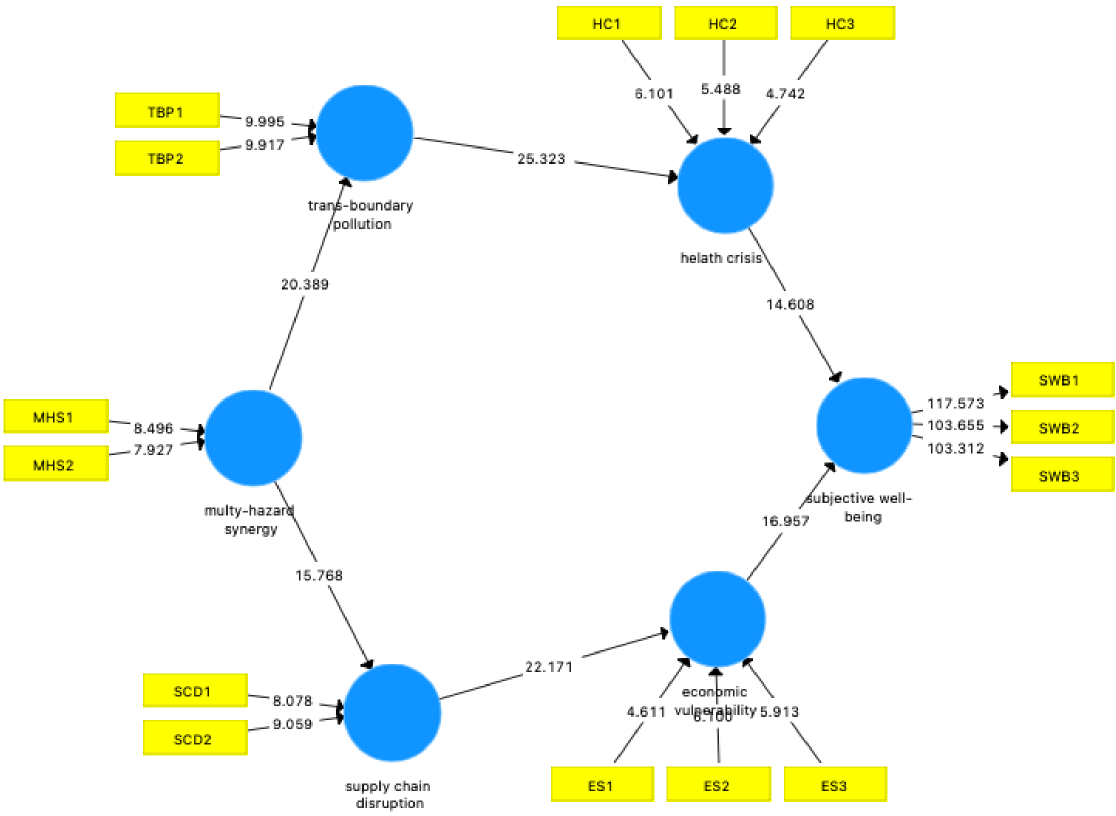


Figure 5. Empirical Structural Model – Sumatera



In the NTT model, all seven hypothesized direct paths were significant ($p < 0.01$). Perceived Drought Chronicity was associated with greater Water Insecurity (beta = 0.880) and lower Livelihood Resilience (beta = -0.361); Water Insecurity was associated with lower Food Security (beta = -0.672), while Food Security was associated with lower Mental Health Stress (beta = -0.512). Livelihood Resilience was associated with lower Economic Vulnerability (beta = -0.347), and the NTT Subjective Well-Being profile was negatively associated with Mental Health Stress (beta = -0.752) and Economic Vulnerability (beta = -0.089). These direct paths are consistent with the proposed chronic-attrition configuration but do not test the multi-step indirect chains.

In Sumatera, all six hypothesized direct paths were significant ($p < 0.001$). Perceived Multi-Hazard Synergy was associated with Perceived Trans-Boundary Pollution (beta = 0.573) and Supply Chain Disruption (beta = 0.514), which were associated with Health Crisis (beta = 0.639) and Economic Vulnerability (beta = 0.586), respectively. Health Crisis (beta = -0.434) and Economic Vulnerability (beta = -0.464) were negatively associated with the Sumatera Subjective Well-Being profile. These direct-path estimates are consistent with two modeled routes, but they do not establish temporal causation, equal indirect effects, or comparability with the NTT endpoint.

Table 13. Descriptive Multi-Step Path Products Derived from Reported Direct Coefficients

Context	Modeled Multi-Step Chain	Arithmetic Path Product	Non-inferential Reading
NTT chronic drought	DC → WI → FS → MH → SWB	-0.228	Larger descriptive product within the NTT model

NTT chronic drought	DC → LR → EV → SWB	-0.011	Smaller descriptive product within the NTT model
Sumatera multi-hazard	MHS → TBP → HC → SWB	-0.159	Descriptive pollution-health chain
Sumatera multi-hazard	MHS → SCD → ES → SWB	-0.140	Descriptive supply-chain-economic chain

Note: Each coefficient is the exact product of the reported constituent path coefficients. The values summarize the modeled chains and their relative magnitudes; they do not replace case-level bootstrap confidence intervals, which cannot be reconstructed from the aggregate path table alone.

4.5. Cross-Context Comparative Pattern Analysis

Because the regional models differ in constructs, indicators, paths, and Subjective Well-Being content, Table 13 is interpreted only within each model. In NTT, the arithmetic products are -0.228 for the resource-stress chain and -0.011 for the livelihood-economic chain; in Sumatera they are -0.159 for the pollution-health chain and -0.140 for the supply-chain-economic chain. These point differences are descriptive. Without bootstrapped specific indirect effects or pairwise contrasts, the study does not claim that one route is statistically dominant, that two routes are statistically balanced, or that either regional architecture differs because of hazard type.

4.6. Supplementary and Control Analyses

To reduce common-method risk, the study used neutral wording, assured anonymity, separated construct blocks in the interview flow, trained enumerators, and applied independent back-checking. The reported statistical assessment combined a marker-variable technique with Harman's single-factor test: the marker variable was reported as having no significant association with the substantive constructs, and the first unrotated factor accounted for 28.7% of the variance. Harman's result is treated only as supplementary evidence rather than a decisive test. The maximum reported structural VIF was 2.87, indicating no critical inner-model collinearity under the stated criterion (Yana et al., 2015).

The marker construct, item wording, theoretical rationale, reliability, and coefficients were not retained in the available analytical output, so the marker result cannot be independently evaluated. VIF addresses structural collinearity rather than method variance, and same-respondent negative affect may still inflate covariance among water anxiety, food insecurity, mental stress, vulnerability, and well-being.

4.7. Discussion

This study identifies two context-specific vulnerability configurations estimated in separate, non-equivalent regional models. The contribution lies not in proposing universal models or statistically attributing regional differences to hazard type, but in specifying how hazard temporality, livelihood dependence, resource buffering, and system interdependence may condition different pathway configurations. The findings align with work on drought-related scarcity and multi-hazard disruption (Sharma et al., 2023; Weston et al., 2015), while extending that literature through an explicit but carefully bounded comparison of modeled pathway shapes. Because measurement, population composition, institutions, timing, and recent-event exposure differ across the cases, the analysis does not isolate hazard regime as the statistical cause of the contrast.

Socio-demographic and institutional heterogeneity. Tables 3 and 4 show differences in age, gender, education, household size, and farming experience. These characteristics were not included as controls or examined in sensitivity analyses. Baseline poverty, livelihood dependence, institutional capacity, social capital, safety nets, service quality, and pre-existing distress may therefore account for part of the observed differences. Hazard regime is one theoretically plausible explanation among several, not an isolated causal factor.

4.7.1. The Chronic Stress Pathway (NTT)

In NTT, repeated drought pressure is associated with a predominantly sequential configuration. The strong drought–water insecurity relationship is theoretically plausible where agriculture and livestock depend on rainfall and where storage, irrigation, and alternative sources provide limited buffering (Liu et al., 2018; Martin et al., 2021). Persistent scarcity repeatedly activates the same household coping demands, so the relevant mechanism is cumulative burden rather than a single shock.

Water insecurity is associated with lower Food Security, which is then associated with greater Mental Health Stress. This pattern is consistent with cumulative scarcity: households must repeatedly allocate time and money to water acquisition, adjust consumption, and protect production, gradually exhausting material and psychological coping resources (Asiamah et al., 2025; Dadson et al., 2017; Perrone & Hornberger, 2014; Shao & Yu, 2023; Tan et al., 2021). Mental Health Stress has the largest direct association with well-being in the NTT model, but the measure captures self-reported anxiety, hopelessness, and sleep interference rather than a clinical diagnosis. Institutional buffering, social support, and pre-existing distress remain plausible competing explanations (Cianconi et al., 2020; Cunsolo & Ellis, 2018; Lawrance et al., 2022; Rafa et al., 2025).

The negative paths involving Livelihood Resilience are coherent once scoring is clarified: greater perceived drought chronicity is associated with lower resilience, and higher resilience is associated with lower economic vulnerability. The arithmetic product for the livelihood-economic branch is smaller than that for the resource-stress chain in the reported NTT coefficients. Because specific indirect effects and their uncertainty were not bootstrapped, this difference is descriptive and does not establish statistical dominance. It may be consistent with coping exhaustion and dependence on foundational resources, but reverse causality, baseline poverty, timing, and unmeasured institutional support cannot be excluded.

4.7.2. Multi-Hazard Context (Sumatera)

In Sumatera, the architecture is more dispersed because interacting hazards can interrupt several interdependent systems at once. Pollution can burden health services and household functioning, while damaged transport and market access can interrupt agricultural supply chains. System interdependence therefore provides a mechanism for parallel rather than purely sequential vulnerability (Zscheischler et al., 2020).

The arithmetic path products are -0.159 for the pollution-health chain and -0.140 for the supply-chain-economic chain. Their proximity is consistent with concurrent health and economic pressures (Djalante et al., 2017; Sovacool et al., 2021; Watts et al., 2019; Zhang et al., 2017), but no bootstrapped indirect-effect estimates or statistical contrast is available. The products therefore cannot establish that the routes are equally strong or balanced, and differences in public services, prior exposure, household assets, interview timing, or reporting practices may also contribute.

The Sumatera configuration therefore illustrates how limited redundancy across transport, markets, and health services may transmit stress through multiple nodes. This interpretation extends cascading-risk theory to household well-being, while remaining conditional on the sampled regions and the constructs included in the model.

Taken together, the significant direct paths are consistent with simultaneous socio-economic and health-related disruptions in the Sumatera sample. This interpretation remains conditional on the indicators included in the model and does not demonstrate mediation through either complete chain.

4.7.3. Differentiated Vulnerability Pathways

The comparative analysis organizes two context-sensitive, within-model configurations rather than statistically interchangeable architectures. Chronic attrition is proposed where scarcity is persistent, livelihoods depend on climate-sensitive resources, and household or institutional buffers are weak. Cascading disruption is proposed where perceived hazards interact across tightly coupled infrastructure, health, and market systems with limited redundancy. These are theory-consistent interpretations for future testing, and hybrid configurations remain possible.

The theoretical distinction links hazard conditions to possible transmission mechanisms while preserving the study's inferential limits. Because the regional models lack common measurement, invariant indicators, equivalent endpoints, controls for sample composition and timing, and objective exposure linkage, the study does not statistically prove that one coefficient or configuration is stronger than another. Its contribution is the specification of testable mechanisms and scope conditions for future longitudinal and multi-context research (Doherty & Clayton, 2011; Mongonia, 2022).

To synthesize the two empirically grounded archetypes, Table 14 contrasts their mechanisms, scope conditions, and adaptation priorities. The labels organize the observed configurations and should not be read as exhaustive classifications.

Table 14. Context-Sensitive Vulnerability Configurations and Their Characteristics

Dimension	**Chronic Attrition Configuration (NTT)**	**Cascading Disruption Configuration (Sumatera)**
Core Logic	Cumulative scarcity and coping exhaustion	Parallel disruption across interdependent systems
Modeled route	Resource insecurity and psychosocial stress	Concurrent health and economic routes
Modeled Organization	Sequential chain; cumulative interpretation	Parallel routes; cascading interpretation
Resilience Target	Water, livelihood, and coping buffers	Redundancy across health, markets, and infrastructure
Justice Dimension	Distributive and recognitional	Procedural, distributive, and restorative
Plausible Policy Priority	Resource security and non-clinical psychosocial support	Supply-chain resilience and public-health buffering

As shown in Table 14, the NTT model contains a more sequential set of direct paths, whereas the Sumatera model contains parallel health and economic routes. The contrast is a theoretical summary of the variables and paths specified in each model, not a formal comparison of equivalent constructs, temporal sequences, or indirect effects.

This comparison highlights that vulnerability depends not only on exposure intensity but also on the way stress is transmitted through livelihood and service systems. In agriculture- and livestock-dependent settings, chronic drought can progressively constrain water, feed, and food production, while interacting hazards can disrupt supply chains, animal and human health services, and market access at the same time.

These patterns are best interpreted as context-sensitive archetypes that may vary across places and over time. Their external value lies in the explicit mechanisms and scope conditions they propose, which require longitudinal and multi-context validation before broader generalization.

These patterns are best interpreted as provisional, context-sensitive archetypes that may vary across places and over time. Their value lies in the mechanisms and scope conditions they propose; broader generalization requires common measures, objective exposure indicators, temporal controls, and longitudinal multi-context validation.

4.7.4. Implications and Scope of Inference

The findings suggest context-specific priorities rather than demonstrating the effectiveness of particular interventions. In drought-prone settings, the observed configuration points to resource insecurity and non-clinical mental-health stress as plausible areas for attention alongside production and water management, while the Sumatera configuration points to simultaneous health and economic pressures.

Potential responses such as reliable water access, livelihood buffering, psychosocial support, stronger public-health capacity, supply-chain resilience, and emergency buffers should be treated as policy options motivated by the observed pathway configurations and prior literature. Their effectiveness was not tested in this cross-sectional study and requires independent evaluation.

The models support direct associations and non-inferential multi-step path summaries within each context. They do not establish causality, mediation, clinical outcomes, cross-regional measurement equivalence, intervention effectiveness, or hazard-regime effects. Future research should use longitudinal data, common measures, objective indicators, measurement-invariance testing, bootstrapped specific indirect effects, and theoretically justified demographic and institutional controls.

5. Conclusion and Suggestion

This study reports two observed within-model configurations. In NTT, perceived drought chronicity is associated with water insecurity, food security, mental health stress, livelihood resilience, economic vulnerability, and an NTT-specific well-being profile. In Sumatera, perceived multi-hazard interaction is associated with pollution-health and supply-chain-economic routes terminating in a differently measured well-being profile. The results do not establish that hazard type statistically explains the contrast between the two configurations.

The findings are consistent with a context-sensitive, mechanism-based view of vulnerability: chronic attrition may be relevant where climate-sensitive livelihoods face weak resource and institutional buffers, while cascading disruption may be relevant where hazards affect interconnected health, infrastructure, and market systems. These propositions remain conditional on the measures, populations, and timing of the present study.

The proposed labels should therefore be treated as provisional archetypes rather than universal or statistically equivalent regional models. Given the cross-sectional, same-respondent, and perceptual design, the findings indicate associations rather than causality, diagnosis, mediation, or verified intervention effects. Policy options involving resource security, psychosocial support, public-health capacity, and supply-chain resilience should be evaluated independently before claims of effectiveness are made.

6. Limitations and Future Research

Several limitations should be acknowledged. First, the cross-sectional design limits causal and temporal inference; the May-December 2025 fieldwork window was not a controlled seasonal comparison, and interview month and proximity to recent events were not included as covariates. Second, reliance on self-reported measures may introduce recall, mood, and social-desirability biases; the hazard constructs were not linked to site-matched objective exposure records. Third, the two regional models use different constructs and non-equivalent Subjective Well-Being indicators, so the results support two within-model patterns rather than a statistical explanation of cross-context differences. Fourth, detailed district-village sampling flow, refusals, replacements, and response rates are unavailable. Fifth, socio-demographic and institutional differences were not controlled, leaving population composition, poverty, services, social capital, safety nets, and prior distress as alternative explanations. Sixth, the reflective specification remains questionable for composite-like constructs, while complete Fornell-Larcker and HTMT matrices with bootstrap intervals are not available. Seventh, same-respondent measurement remains vulnerable to common-method and negative-affect covariance; Harman's test is supplementary, and the reported marker-variable finding lacks the documentation required for independent evaluation. Finally, Table 13 contains descriptive arithmetic path products rather than bootstrapped specific indirect effects, and the available ethics record does not provide a committee name, approval number, or formal exemption.

Future research should combine perceptual measures with objective indicators such as NDVI, soil moisture, PM2.5, disaster-event records, agricultural production data, and health records; examine hybrid environments where chronic degradation and acute shocks overlap; and test institutional support, social capital, adaptive capacity, safety nets, gotong royong, disaster relief, livelihood diversification, and climate-smart technologies as controls or moderators. Common constructs, measurement-invariance testing, reproducible sampling-flow records, verified ethics documentation, temporal controls, bootstrapped specific indirect effects, longitudinal or multi-wave designs, and PLSpredict assessment are also needed before broader generalization.

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Declaration of AI and AI-assisted technologies in the writing process

ChatGPT was used solely for English language checking and refinement, with all content reviewed and approved by the authors.

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