Household Resilience to Climatic Shocks across Farm-System Types in Bangladesh

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Abstract

Evidence is still limited on the differential resilience of households in different farming systems in Bangladesh, despite the fact that climate-related shocks impact livelihoods. This study compares resilience between specialised crop, specialised livestock and mixed crop–livestock households and investigates whether resilience differences across farm-system types vary with climatic shock such as floods, droughts and cyclones. The analysis is based on a two-round panel of 1,462 households from the FAO Data in Emergencies Monitoring programme, which provides 2,924 household-round observations. The RIMA-II framework estimates a Resilience Capacity Index based on four pillars: Access to Basic Services, Assets, Social Safety Nets, and Adaptive Capacity, and a Multiple Indicators Multiple Causes model. 2,444 observations are used in weighted pooled regressions with survey-round fixed effects and household-clustered standard errors. Mixed crop–livestock households have significantly higher resilience scores than specialised crop households under non-shock conditions. This gap is much greater for households that report climatic shocks, and the overall mixed versus crop gap under shock exposure is statistically significant. Specialised livestock households have much lower resilience scores than specialised crop households in non-shock conditions but are not significantly different in shock exposure conditions. The results show associations between farm-system type, climatic shocks, and household resilience capacity, but do not imply causal effects.

Keywords: *household resilience, climatic shocks, farm-system types, mixed crop–livestock systems, RIMA-II, Bangladesh.*

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1. Introduction

Food insecurity and agricultural vulnerability are major issues that affect the welfare and livelihoods of rural households in Bangladesh (Bishwajit et al., 2014). Bangladesh is a deltaic country and is one of the top ten climate change-vulnerable countries in the world (Rahman and Lateh, 2017). Agricultural production is still affected by climatic shocks such as floods, droughts, cyclones and salinity intrusion (Bangladesh Bureau of Statistics [BBS], 2016). Climate-sensitive crop production is a risk to household food security, rural livelihoods and the resilience of farming communities. Climate models predict that global warming will have a major impact on crop yields. Climate change has already adversely affected the yields of some crops, including maize and wheat, in many lower-latitude areas (Mbow et al., 2019). Climate variability and extremes are projected to continue to affect crop and livestock production and food security, especially in sensitive agricultural areas (Thornton et al., 2014; Intergovernmental Panel on Climate Change [IPCC], 2023). Food insecurity remains a major issue in Bangladesh, particularly for rural households whose livelihoods are vulnerable to climate change (Integrated Food Security Phase Classification [IPC], 2024). Agriculture, forestry and fishing accounted for around 11.38% of the GDP of Bangladesh in fiscal year 2022-2023, where crops and horticulture accounted for around 5.51% (BBS, 2024). Recurrent climatic shocks, high food prices, and low-income opportunities exacerbate this vulnerability (IPC, 2024). The resilience of farms to climatic shocks is an emerging research area. Adaptive capacity and resilient food systems are key to maintaining livelihoods in the face of future climate risks. Climate change causes greater fluctuations in rainfall, temperature, and extreme events, directly threatening agricultural productivity and food security (Pret et al., 2025). Resilience is traditionally defined as the capacity of a system to recover from a disturbance, but more recent views emphasize adaptation and transformation in response to changing conditions (Davoudi et al., 2012; Scott, 2013). Resilient food systems can adapt to new conditions, continue to produce food, and provide access to food for vulnerable populations. These systems help to reduce the effects of shocks and stressors, and social and economic factors also play a role in resilience (Tasnim et al., 2025). Household productive activity organisation and diversification can be used to measure agricultural resilience. For instance, crop diversification lowers the risk of environmental fluctuations and increases production stability (Lin, 2011). In general, agricultural diversification can provide socioeconomic and environmental advantages for sustainable and climate-resilient production systems (Raveloaritiana & Wanger, 2026). In this thesis, I compare the resilience of farms across different farm types, with comparisons made between crop-only, livestock-only, and mixed crop-livestock households. Mixed crop-livestock farms can improve resilience by providing crop–livestock resource cycling, diversifying food and income sources, and providing livestock portfolios to buffer household income and consumption during climatic stress (Herrero et al., 2010; Thornton & Herrero, 2015; Acosta et al., 2021).

The aim of this thesis is to examine the variation in household resilience capacity between crop-only, livestock-only and mixed crop-livestock households in Bangladesh and the relationship between this variation and reported exposure to climatic shocks. The research question of this study is whether there is any difference in the household resilience capacity between the crop-only, livestock-only and mixed crop-livestock households in Bangladesh and what are the linkages between the difference in the capacity and reported exposure to climatic shocks.

2. Literature Review and Conceptual Framework

The Resilience Index Measurement and Analysis (RIMA) framework has been used in previous studies to explore the multi-dimensional nature of household resilience in different contexts. Ngesa et al., (2021) demonstrate that the relative importance of resilience pillars varies across Eastern African settings, and Mossie et al., (2024) use a cross-sectional RIMA-based analysis to explore household resilience to food insecurity in rural Ethiopia. While these studies emphasize the general importance of multidimensional resilience measurement, they do not consider the differences between farm-system types in Bangladesh.

Household resilience, climatic shocks and agricultural diversification have been studied in Bangladesh using different analytical methods. Smith and Frankenberger (2018) use pre- and post-flood data to examine if household resilience capacities reduced the negative impacts of flooding on food security. Islam et al., (2018) explore the link between farm diversification and food and nutrition security using nationally representative household panel dataset. Matsuura-Kannari et al., (2023) investigate the links among weather shocks, crop and income diversification, and household food security. More recently, Tasnim et al., (2025) use RIMA to estimate resilience capacity in rural Bangladesh based on data from one survey year.

However, there is still limited evidence on the multidimensional resilience capacity of different types of farm-systems and climatic-shock exposure in Bangladesh. This study contributes to the literature in three ways. First, it directly compares the resilience capacity of crop-only, livestock-only and mixed crop–livestock households. Second, it examines whether these differences are associated with self-reported exposure to climatic shocks. Third, it develops a RIMA-II based resilience index based on harmonised two-round DIEM data and tests its concurrent validity with dietary and experience-based food-security indicators.

This section reviews the concepts and evidence that provide the theoretical foundation for the study. Section 2.1 explains the measurement of household resilience, while Section 2.2 discusses farm-system diversification and the potential role of mixed crop–livestock systems.

2.1 Measuring Resilience

The Resilience Index Measurement and Analysis II (RIMA-II) framework conceptualises household resilience to food insecurity. RIMA-II defines resilience capacity as a multidimensional latent construct that cannot be directly observed but can instead be estimated using observable household characteristics and capacities (Food and Agriculture Organization

of the United Nations [FAO], 2016). The household is an appropriate unit of analysis, as decisions about food consumption, livelihood activities and responses to shocks are typically made at this level. Thus, decisions made at the household level have implications for food insecurity. This framework is especially pertinent in rural Bangladesh, where climatic shocks often threaten household livelihoods and food security.

Resilience can be defined as the ability of farms and farming systems to continue to perform their core functions under economic, social, environmental and institutional shocks and stresses. Meuwissen et al. (2019) describe resilience of farming systems as being robust, adaptable and transformable. Robustness is the ability to withstand shocks and continue to perform current functions, adaptability is the ability to modify practices and strategies to meet changing conditions, and transformability is the ability to make more fundamental changes when existing configurations are no longer viable. Slijper et al. (2022) also conceptualise farm resilience as a dynamic ability to deal with uncertainty and adapt to changing environments. Resilience is not just about resisting disturbances; it is also about adapting the use and organisation of resources and livelihood activities to changing conditions. This perspective offers a more general conceptual understanding of resilience and is used in this study to operationalise resilience in the RIMA-II framework.

RIMA-II organises the observable determinants of household resilience into four principal pillars (FAO, 2016):

- *Access to Basic Services (ABS)*: This pillar refers to the availability and accessibility of basic services and infrastructure, such as health care, education, markets, water, sanitation and electricity. Access to these services supports household welfare, facilitates income generation, and enhances the capacity to respond to shocks.
- *Assets (AST):* This pillar includes productive and non-productive assets including land, livestock, agricultural equipment, savings and other assets. These assets help in production, consumption smoothing, and household recovery after negative events.
- *Social Safety Nets (SSN):* This pillar includes both formal and informal transfers or assistance, including government programmes, non-governmental organisations, remittances, and social networks. While this support can help households cope with the immediate welfare losses, observed relationships may also be due to the targeting of assistance to vulnerable households.
- *Adaptive Capacity (AC):* This pillar captures the capacity of households to adapt their livelihood strategies to changing conditions. These are education, livelihood and income diversification, access to information and household labour.

These pillars can help to make a household resilient, but they are not guarantees. The relative importance of these depends on the indicators used, the population studied, the livelihood system and the nature of the shock exposure.

There is a difference between resilience capacity and food-security outcomes. Resilience capacity is the resources and capabilities that are likely to enable households to be resilient, adapt to or recover from shocks, while food security is a welfare outcome that resilience capacity may help to protect. To prevent resilience being used as a proxy for food security, research on resilience has increasingly focused on measuring the two concepts separately

(Ansah et al., 2019). RIMA-II adopts this distinction by estimating the resilience capacity of households based on the pillars of resilience and then exploring the link between resilience and food-security outcomes (FAO, 2016).

RIMA applications show that the estimated associations between resilience pillars and household resilience vary across contexts, such as Eastern Africa, where the resilience capacity differed across regions and livelihood systems (Ngesa et al., 2021). In Karamoja, Uganda, Adaptive Capacity and Assets were identified as important dimensions of household resilience, with income diversification, education and productive assets supporting these dimensions (FAO, 2018). Using three waves of panel data from Tanzania and Uganda, d'Errico et al., (2018) found that Adaptive Capacity had the strongest association with household resilience and that higher initial resilience capacity was associated with better future food security and a greater capacity to recover from shocks. In northern Ethiopia, Adaptive Capacity, Assets and Social Safety Nets were positively associated with resilience, whereas Access to Basic Services had a negative association (Mossie et al., 2024). To summarise, these findings demonstrate that estimated pillar associations are context specific.

Evidence from research specific to Bangladesh is particularly relevant. The data collected before and after the 2014 floods in northern Bangladesh suggest that livelihood diversity, asset holdings, social safety nets, access to markets and services, and various absorptive, adaptive, and transformative capacities mitigated the negative impacts of flooding on household food security (Smith and Frankenberger, 2018). The authors, however, described this evidence as suggestive, not necessarily causal (Smith and Frankenberger, 2018). RIMA-II was not used in this study, but it does emphasize the need to consider household resilience capacities when they are exposed to climatic shocks. Tasnim et al. (2025) applied RIMA-II in Bangladesh and found that household resilience capacity was positively associated with access to basic services, land assets and farm equipment, while adaptive capacity was positively but not statistically significantly associated. Livestock assets were negatively associated with resilience, possibly due to market volatility, disease exposure, maintenance costs, and climatic vulnerability (Tasnim et al., 2025). These findings suggest that the contribution of a resource is dependent on the type of resource, management needs, and contextual risks.

Food-security indicators can be used to assess whether an estimated resilience index is meaningfully related to household welfare. The Household Dietary Diversity Score is a measure of the number of food groups consumed by a household and gives a snapshot of household access to a diversity of foods (Kennedy et al., 2011). Other dimensions of food access and deprivation are captured by experience-based food-insecurity and hunger measures. These indicators can thus be used to assess the relationship between estimated resilience capacity and food-security outcomes without assuming that they are synonymous.

There are some remaining methodological difficulties in measuring resilience, such as variation in the definitions, indicators, and estimation approaches used in studies, making it difficult to compare resilience scores across contexts (Ansah et al., 2019). Different measurement methods or indicators can identify different households as resilient, and they have limited predictive power for future food-security outcomes (Upton et al., 2022). These restrictions highlight the importance of a well-defined multidimensional framework, clear indicator selection, and

additional validation with related food-security indicators. Below, I describe how I have addressed these issues in this thesis.

2.2 Farm-System Diversification, Mixed Crop–Livestock System

Diversity and redundancy are well known attributes of resilient social–ecological systems because various components can react differently to the same disturbance (Meuwissen et al. 2019). Diversity and redundancy are therefore a general rule for improving a system's ability to operate under varying conditions (Biggs et al., 2015). In agriculture, this means that households engaged in several productive activities can better maintain their livelihoods if one of the activities is negatively impacted. Crop diversification is an example of this principle. Diversified cropping systems can increase the farm's capacity to deal with environmental variability by spreading the production risks among different crops or varieties (Lin, 2011). This study goes beyond the diversification argument and compares crop-only, livestock-only, and mixed crop–livestock households. Mixed crop–livestock systems are especially relevant because crops and livestock have complementary production and livelihood functions. Crop residues can be used for livestock feed, livestock can be used for manure, food, income, traction, and saleable assets. These interactions render mixed crop–livestock systems important for global food production and smallholder livelihoods (Herrero et al., 2010).

Resource cycling and economic complementarity are part of the resilience benefits of integration. A comparison of mixed and specialised farms in France showed that the mixed systems lowered some production costs and were less sensitive to input and output price fluctuations than some specialised systems. But significant variations in management and performance were found between farms in the same production system (Ryschawy et al., 2012).

Livestock can be used to produce extra food and income and can be an asset that can be sold in times of stress. The effectiveness of livestock as a coping mechanism, however, is dependent on the species and composition of the household's livestock portfolio (Acosta et al., 2021). At the farm level, data from Africa suggest that integrated farms may be more profitable than specialised farms under some of the projected climate scenarios, depending on the climate projection (Seo, 2010).

The literature on climate adaptation highlights several strategies for mixed systems to adapt to climate change. Adaptation options in mixed systems involve changes in crop management, livestock management, feeding strategies, and the relationship between crop and livestock enterprises (Thornton and Herrero, 2015). These strategies can provide households with more flexibility in adapting the use of farm resources to changing climatic and production conditions. The evidence from northern Namibia indicates that diversification of crop and livestock production can be an adaptation strategy and improve household food security. However, the benefits differ among households and depend in part on access to climate information and other enabling resources (Mulwa and Visser, 2020). This evidence suggests that agricultural diversification may be beneficial, but it does not prove that all mixed households are more resilient than specialised households.

Studies specific to Bangladesh provide additional evidence on the relationship between diversification and food-security outcomes. Using two waves of nationally representative household panel dataset, analysis showed that farm-production diversification was positively associated with household dietary diversity, but the association was relatively small. Market access, off-farm income diversification and women empowerment were also important, indicating that production diversity alone may not be enough to make significant dietary changes (Islam et al., 2018). Weather shocks affected crop and income diversification, both linked to food expenditure but not consistently to dietary diversity. Income diversification benefited wealthier households more (Matsuura-Kannari et al., 2023). However, existing studies have not compared resilience across different farm-system types.

Mixed farming is a potentially valuable but context dependent climate-adaptation strategy, as recently presented in literature. Diversification in mixed systems can help mitigate climate risks and enhance livelihood resilience, food security, and various farm functions. The effectiveness of these systems, however, is dependent on socioeconomic, institutional and biophysical conditions, and the quality of farm management (Baker et al., 2023). Mixed farming should therefore be seen as a potential source of resilience, but not necessarily more resilient in all situations.

While RIMA-II has been applied to the study of household resilience and food security in rural Bangladesh, no study has compared the resilience of crop-only, livestock-only, and mixed crop-livestock households (Tasnim et al., 2025). Likewise, the Bangladesh diversification studies reviewed here are concerned with production diversification, income diversification, or food-security outcomes, but not with differences in multidimensional resilience capacity across farm-system types. This gap poses an important question: do specialised and mixed farm households differ systematically in their resilience capacity when exposed to climatic shocks? This thesis aims to fill this gap by comparing crop-only, livestock-only and mixed crop–livestock households in Bangladesh using a RIMA-II based Resilience Capacity Index.

3. Data: Data in Emergencies Monitoring (DIEM)

The Data in Emergencies Monitoring (DIEM-Monitoring) system was developed by the Food and Agriculture Organisation of the United Nations (FAO) to gather and share timely information on shocks, agricultural livelihoods, food production and food security in crisis prone areas. FAO has carried out several rounds of DIEM household surveys in Bangladesh. I use data from Round 6 and Round 7 because these rounds contain identifiable repeated households and have variables that are sufficiently comparable to create the necessary indicators.

Round 6 was held from 7 September to 8 October 2022, and Round 7 from 17 February to 21 March 2023. Both surveys used structured questionnaires that were conducted by computer-assisted telephone interviews. The dataset contains household characteristics, agricultural activities, income sources, assistance, food security, coping behaviour, and self-reported exposure to shocks. The agricultural modules recorded household involvement in crop and

livestock production and constraints to production and marketing. Climatic-shock exposure is measured by household reports of floods, droughts, and hurricanes/cyclones in the reference period.

The resulting dataset contains only households that were observed in both survey periods, representing a balanced panel dataset. There were 2,546 observations in Round 6 and 3,075 observations in Round 7, totalling 5,621 observations prior to panel data matching. The balanced panel data set includes 1,462 households observed in each round, for a total of 2,924 household-round observations. As a result, 1,084 observations were excluded from Round 6, and 1,613 observations were excluded from Round 7 because they were not matched between the two rounds. The panel data set covers a wide geographical area, but the sample is limited to respondents who participated in more than one survey, which may impact the representativeness of the analytical sample relative to the original cross-sectional surveys.

Numeric and count variables are standardized using the pooled means and standard deviations from both rounds, after being directionally recoded. This is done because the RIMA indicators are on different scales, such as land-size categories, livestock counts, income-change scores, dietary diversity scores, and food-insecurity scores. Without standardization, variables with larger ranges of numbers could have a larger influence on the resilience index simply because of the range of numbers. I am standardizing using z-scores:

$$z_{it} = \frac{x_{it} - \bar{x}}{s_x}$$

where x_{it} is the original value of variable x for household i in round t, $\bar{x}$ is the pooled mean of the variable across both rounds, and s_x is the pooled standard deviation. Following binary recoding, the retained binary and numeric indicators were standardized using pooled means and standard deviations from the two-rounds. Table 1 provides an overview of the variables used in the analysis.

Table 1: Variable dictionary

Variable name	Description and interpretation	Resilience pillar	Min	Max
Crop irrigation access	Binary indicator equal to 1 when the household uses an irrigation source for its main crop and 0 when production is rainfed. Higher values indicate better access to irrigation.	Access to Basic Services (ABS)	-2,580	0,387
No crop production difficulty	Binary indicator equal to 1 when the household reports no difficulty producing crops and 0 when it reports a difficulty. Higher values indicate more favourable crop-production conditions.	Access to Basic Services (ABS)	-1,188	0,842
No crop sales difficulty	Binary indicator equal to 1 when the household reports no difficulty selling crops and 0 when it reports a difficulty. Higher values indicate more favourable crop-marketing conditions.	Access to Basic Services (ABS)	-2,608	0,383

No livestock production difficulty	Binary indicator equal to 1 when the household reports no difficulty producing or raising livestock and 0 when it reports a difficulty. Higher values indicate more favourable livestock-production conditions.	Access to Basic Services (ABS)	-1,405	0,712
No livestock sales difficulty	Binary indicator equal to 1 when the household reports no difficulty selling livestock or livestock products and 0 when it reports a difficulty. Higher values indicate more favourable livestock-marketing conditions.	Access to Basic Services (ABS)	-3,448	0,290
Household land size	Cultivated land area harmonised across the two survey rounds into comparable land-size categories. Higher values indicate greater access to land.	Assets (AST)	-0,633	3,465
Current livestock holdings	Current number of livestock owned or raised, transformed to reduce the influence of extremely large holdings. Higher values indicate larger livestock holdings.	Assets (AST)	-1,744	7,988
Change in livestock holdings	Change in the number of livestock relative to the previous reference period. Higher values indicate an increase in livestock holdings, while lower values indicate a decrease.	Assets (AST)	-4,563	5,784
Fishing activity	Binary indicator showing whether the household participates in fishing or aquaculture activities. Higher values indicate participation in fishing or aquaculture.	Assets (AST)	-0,434	2,305
Assistance received	Binary indicator showing whether the household received food, cash, vouchers, agricultural inputs, or another form of assistance.	Social Safety Nets (SSN)	-0,509	1,963
No assistance need	Binary indicator equal to 1 when the household reports no need for assistance and 0 when it reports needing assistance. Higher values indicate no reported assistance need.	Social Safety Nets (SSN)	-0,507	1,971
No cash assistance need	Binary indicator equal to 1 when the household reports no need for cash assistance and 0 when it reports needing cash assistance. Higher values indicate no reported cash-assistance need.	Social Safety Nets (SSN)	-0,695	1,439
No marketing support need	Binary indicator equal to 1 when the household reports no need for marketing support and 0 when it reports needing such support. Higher values indicate no reported marketing-support need.	Social Safety Nets (SSN)	-9,126	0,110
Number of income sources	Number of valid household income sources reported during the previous three months. Higher values indicate greater income diversification.	Adaptive Capacity (AC)	-0,937	1,728
Main income change	Change in income from the household's primary source relative to the reference period, ranging from a substantial decrease to a substantial increase. Higher values indicate a more favourable income change.	Adaptive Capacity (AC)	-2,182	2,255
Household dietary diversity score	Number of food groups consumed by the household. Higher values indicate greater household dietary diversity.	Food security measurement	-2,217	2,622

Reverse-coded FIES score	Food Insecurity Experience Scale score recoded so that higher values indicate lower food insecurity. Used only for supplementary validation.	alternative/validation indicator, not used in final SEM	-1,987	0,990
Reverse-coded household hunger score	Household Hunger Scale score recoded so that higher values indicate less household hunger. Used only for supplementary validation.	alternative/validation indicator, not used in final SEM	-4,998	0,596
Moderate food insecurity probability	Estimated probability that the household experiences moderate or severe food insecurity. Higher values indicate greater food-insecurity risk. Used only for supplementary validation.	Food security validation	-0,831	1,525
Severe food insecurity probability	Estimated probability that the household experiences severe food insecurity. Higher values indicate greater severe-food-insecurity risk. Used only for supplementary validation.	Food security validation	-0,303	5,896

The balanced panel allows for two observations of each household, and thus allows for the observation of household conditions, farm-system status and reported shock exposure at two points in time. The regression models, however, do not include household fixed effects and do not estimate household-specific resilience trajectories, and do not fully control for time-invariant household characteristics; section 4.2 discusses the rationale for this modelling choice. Survey identifiers, round indicators, interview dates and geographic identifiers were kept for harmonization, descriptive analysis and model specification.

Farm-system type is determined independently for each survey round based on participation in agricultural activities reported. Households that report crop production but not livestock production are considered specialized crop households, while households that report livestock production but not crop production are considered specialized livestock households, and households that report both activities are considered mixed crop–livestock households. In Round 6, there are 336 specialized crop, 331 specialized livestock and 655 mixed crop–livestock households among observations eligible for these three categories. There are 345 specialized crop, 253 specialized livestock and 527 mixed crop–livestock households in Round 7. There is variation in farm-system status observed between rounds, as some households move from one category to another. However, the regression models do not account for household fixed effects, so the estimated associations are a mix of within-household and between-household variation and could still be due to time-invariant household differences. Observations not in the three categories are not included in the farm-system regressions and are not part of the specialized-crop reference group. Farm-system classifications are not included in the construction of the RCI to avoid a mechanical association with resilience.

Table 1 presents a summary of the variables included in the analysis and their categorisation into the RIMA-II resilience pillars and additional food-security measures. Farm-system categories and self-reported climatic-shock exposure are not included in the construction of the RCI but are introduced only in the second-stage regression analysis. Indicators were directionally recoded as needed to indicate more favourable household conditions with higher values.

The indicators selected are considered as proxies for the theoretical pillars defined by FAO (2016) and are specific to the datasets available. In this study, ABS is defined as irrigation access and no reported agricultural production and marketing constraints. AST documents specific productive assets and livelihood activities. SSN is a composite measure that includes assistance receipt and no assistance reported, cash and marketing-support needs, and AC is a composite measure that includes income-source diversity and reported change in the household's main income source. The pillar estimates are thus only meaningful in the context of the dimensions that can be captured by these available indicators.

4. Empirical Method

The RIMA-II methodology is used in this study to estimate the resilience capacity of households and to analyse the differences between farm-system types when exposed to climatic shocks. The empirical method has two phases. A Multiple Indicators Multiple Causes (MIMIC) model, a type of structural equation modelling, is used to estimate a Resilience Capacity Index (RCI) at the household level in the first stage. In the second stage, the estimated RCI is compared between crop-only, livestock-only and mixed crop–livestock households.

4.1 First Stage: Resilience Capacity Index (RCI)

The first stage analysis is used to develop a Resilience Capacity Index (RCI) for each household based on the RIMA-II framework (FAO, 2016; d'Errico et al., 2018; Ansah et al., 2019). The four main pillars of the latent construct are Access to Basic Services (ABS), Assets (AST), Social Safety Nets (SSN), and Adaptive Capacity (AC). The RCI is not constructed from farm-system classifications or climatic-shock exposure, as these are used as explanatory variables in the second stage analysis. This separation does not rule out the possibility of endogeneity, however, because households may choose to be in one farm system or another because of observed or unobserved characteristics that are also correlated with resilience. The composite scores (ABS, AST, and SSN) are derived from the sum of component indicators and require at least 2 valid observations of indicators per household-round.

$$C_{jit} = \frac{1}{n_{jit}} \sum_{k=1}^{n_{jit}} Z_{jkit}\,, \qquad j \in \{\text{ABS,AST,SSN}\} \qquad (1)$$

where Z_{jkit} represents processed indicator k for household i in survey round t, and n_{jit} denotes the number of available indicators. In the structural equation model, ABS, AST, and SSN enter as single-indicator latent variables with factor loadings fixed to unity ($\lambda = 1.0$) and residual variances constrained to zero ($\psi = 0.0$), This approach treats each composite as if it is measured without error (Bollen, 1989; Kline, 2016). Adaptive Capacity is defined as a latent variable measured by two observed metrics: the number of income sources and the change in primary income.

$$Z_{\text{AC},kit} = \lambda_{\text{AC},k}\text{AC}_{it} + e_{\text{AC},kit}, \qquad k \in \{1,2\} \qquad (2)$$

where $\lambda_{\text{AC},k}$ denotes the factor loading and $e_{\text{AC},kit}$ represents the measurement error.

The four pillars make up the causal structural part of a Multiple Indicators Multiple Causes (MIMIC) framework (Jöreskog & Goldberger, 1975). The structural equation that connects the pillars to latent resilience capacity is:

$$\text{RCI}^{*}_{it} = \gamma_{\text{ABS}}\text{ABS}_{it} + \gamma_{\text{AST}}\text{AST}_{it} + \gamma_{\text{SSN}}\text{SSN}_{it} + \gamma_{\text{AC}}\text{AC}_{it} + \zeta_{it} \qquad (3)$$

$$\mathrm{FS}_{mit} = \lambda_m \mathrm{RCI}^{*}_{it} + u_{mit} \quad (4)$$

Model selection was dictated by goodness-of-fit parameters (χ^2, CFI, TLI, RMSEA, and SRMR; Hu & Bentler, 1999).

The Household Dietary Diversity Score (HDDS) is used as the food-security indicator in the retained specification to identify the latent resilience construct (Kennedy et al., 2011). For single-indicator identification, the factor loading is set to one and the residual variance to zero. The relationship between the resilience pillars and the latent RCI is estimated using HDDS, but the final household-round RCI scores are only based on the estimated contributions of the resilience pillars. This ensures that the RCI employed in the second stage analysis is not a direct measure of the observed HDDS of each household.

$$\widehat{\mathrm{RCI}}^{\mathrm{capacity}}_{it} = \hat{\gamma}_{\mathrm{ABS}}\widehat{\mathrm{ABS}}_{it} + \hat{\gamma}_{\mathrm{AST}}\widehat{\mathrm{AST}}_{it} + \hat{\gamma}_{\mathrm{SSN}}\widehat{\mathrm{SSN}}_{it} + \hat{\gamma}_{\mathrm{AC}}\widehat{\mathrm{AC}}_{it} \quad (5)$$

This raw pillar-predicted score was min-max normalized to a bounded unit interval $[0,1]$:

$$\mathrm{RCI}_{it} = \frac{\widehat{\mathrm{RCI}}^{\mathrm{capacity}}_{it} - \min\left(\widehat{\mathrm{RCI}}^{\mathrm{capacity}}\right)}{\max\left(\widehat{\mathrm{RCI}}^{\mathrm{capacity}}\right) - \min\left(\widehat{\mathrm{RCI}}^{\mathrm{capacity}}\right)} \quad (6)$$

The normalised index functions as the dependent variable in the second-stage specifications (Equations 7–9).

Pooled maximum likelihood with robust standard errors (MLR) was used to estimate first-stage parameters. Observations from the same household may be correlated since the same households were observed in both survey rounds. While MLR offers robust inference for non-normality, it does not correct for within-household dependence in the pooled specification. The 2,924 household-round observations may thus be treated as independent, which would underestimate the uncertainty of the first-stage estimates. Clustering by region would solve another type of dependence and would not directly addresses the problem of repeated observations of the same household. Thus, the first-stage standard errors, significance tests, and fit statistics should be interpreted with this limitation in mind.

4.2 Second stage: Econometric models

The second stage evaluates the differences in resilience between farm-system types and how this varies with exposure to climatic shocks, after the household-level RCI has been estimated. The econometric approach is built up gradually to distinguish between farm-system differences and the extra contribution of shocks.

The second-stage analysis is limited to household-round observations that are specialized crop, specialized livestock or mixed crop-livestock. Specialized crop households are the reference group and observations not classified in one of these three farm-system groups are not included. Standard errors are clustered at the household level to allow for repeated observations.

The first model in this section, (Equation 7), estimates differences in resilience across farm-system types, but does not account for shock exposure:

$$RCI_{it} = \alpha + \beta_1 LSOnly_{it} + \beta_2 Mixed_{it} + \delta_t + \varepsilon_{it} \quad (7)$$

where RCI_{it} is the estimated Resilience Capacity Index of household $i$in round t. $LSOnly_{it}$ is a dummy variable equal to one if the household is livestock-only, and $Mixed_{it}$is a dummy

variable equal to one if the household is engaged in both crop and livestock production. Crop-only households are used as the reference category. δ_t represents round fixed effects, and ε_{it} is the error term.

In this model, β_1 measures the difference in resilience between livestock-only and crop-only households, while β_2 measures the difference between mixed crop-livestock and crop-only households. If β_2 is positive and statistically significant, it would suggest that mixed crop-livestock households have higher resilience capacity than crop-only households, before explicitly considering shock exposure. A positive coefficient is expected, as integrating crop and livestock activities can provide complementary sources of food, income, feed, manure, and emergency assets, thereby enhancing household resilience (Herrero et al., 2010; Thornton and Herrero, 2015)

The second model (Equation 8) introduces climatic shock exposure as an external stressor:

$$RCI_{it} = \alpha + \beta_1 LSOnly_{it} + \beta_2 Mixed_{it} + \beta_3 Shock_{it} + \delta_t + \varepsilon_{it} \qquad (8)$$

where $Shock_{it}$ is a binary indicator that takes the value of 1 if the household suffered an exposure to any of the climatic shocks considered in the analysis, specifically a flood, hurricane or cyclone-type shock or a drought. The coefficient β_3 reflects the relationship between the exposure to shocks and resilience capacity, controlling for farm-system type and round fixed effect.

This approach matters because climatic-shock exposure is not included when building the RCI. Instead, self-reported climatic-shock exposure is considered an outside stressor and is added separately in the second-stage regression models. Keeping resilience capacity and shock exposure separate follows the RIMA-II framework and matches research on how existing resilience affects food security and recovery after shocks (FAO, 2016; d'Errico et al., 2018; Ansah et al., 2019).

The third and preferred model (Equation 9) adds the interaction between farm-system type and exposure to climatic shocks:

$$RCI_{it} = \alpha + \beta_1 LSOnly_{it} + \beta_2 Mixed_{it} + \beta_3 Shock_{it} + \beta_4 (LSOnly_{it} \times Shock_{it}) + \beta_5 (Mixed_{it} \times Shock_{it}) + \delta_t + \varepsilon_{it} \qquad (9)$$

In this model, the interaction terms are the main variables of interest. The coefficient β_4 measures if the resilience gap between specialized livestock and specialized crop households varies with exposure to climatic shocks. Likewise, β_5 represents the change in the resilience gap between mixed crop-livestock and specialized crop households when exposed to climatic shocks.

The farm-system and shock main effects are kept, as well as the interaction terms. Coefficients in an interaction model are conditional, so that the difference between specialized livestock and specialized crop households under shock exposure is $\beta_1 + \beta_4$, and the difference between mixed crop-livestock and specialized crop households under shock exposure is $\beta_2 + \beta_5$. The multiplicative interaction specification allows the association between climatic shocks and resilience to vary by farm-system type. All constituent main effects are preserved, and the

interaction is understood in terms of conditional effects, not just the interaction coefficient (Brambor et al., 2006).

Thus, the principal hypothesis that mixed crop-livestock households possess a higher resilience capacity than specialized crop households when exposed to climatic-shocks is tested using $\beta_2 + \beta_5$. A positive and statistically significant $\beta_2 + \beta_5$ means that, when both types of households are hit by climatic shocks, mixed crop-livestock households have higher estimated scores than specialized crop households. In contrast, β_5 tests whether the mixed-farming difference is larger under shock exposure than under non-shock conditions.

The three models thus have different applications. The first model is used to estimate the overall differences in resilience between farm-system types. The second model adds shock exposure as an outside stress. The third model examines the moderation of the relationship between shock exposure and resilience by farm-system type. The third model is considered as the preferred specification as itis most closely aligned with the objective.

Standard errors are clustered at the household level for all second-stage models to allow for potential correlation and heteroskedasticity of repeated observations of the same household (Cameron & Miller, 2015). Fixed effects are included to account for common differences between the two survey waves.

To preserve within- and between-household variation, weighted pooled regressions are used. Household fixed effects were not chosen because with only two rounds, farm-system effects would only be identified from households that moved between categories of surveys (Wooldridge, 2010). These changes can be due to short-term farming activity and not structural changes. Fixed effects and household-clustered standard errors are thus applied, and the estimates are interpreted as conditional associations, not causal effects (Cameron & Miller, 2015).

5. Results

This section presents the study results in three stages. First, I compared the MIMIC specifications used to build the Resilience Capacity Index to select the best measurement model. Next, I used the estimated RCI from the first-stage regression models to examine differences in resilience among crop-only, livestock-only, and crop-livestock households. Finally, I have run additional validation checks by comparing the retained score with food-security and coping indicators that were not included in the chosen model.

5.1 MIMIC Model Selection, Pillar Estimates & RCI Distribution

This section is divided into three subsections to present the MIMIC results in a structured and systematic manner.

5.1.1 Selection of the MIMIC specification

Table 2 presents the fit statistics for various MIMIC specifications used to construct the Resilience Capacity Index (RCI). For comparison, the table includes the preferred specification

based on the Household Dietary Diversity Score (HDDS) and alternatives based on the Food Insecurity Experience Scale (FIES), Household Hunger Scale (HHS), and combined food-security indicators. The HDDS-only model demonstrates the best fit to the data. It is admissible and satisfies the primary fit criteria (CFI = 0.987; TLI = 0.935; RMSEA = 0.030; RMSEA close-fit p-value = 0.910).

Table 2: The fit statistics

Model	N	Chi-square	df	CFI	TLI	RMSEA	Close-fit p	SRMR	Admissible	Selected
HDDS only	2924	8.663	3	0.987	0.935	0.030	0.910	0.011	Yes (Best fit)	Yes
FIES only	2924	18.477	3	0.972	0.858	0.047	0.557	0.014	Yes (Poor fit)	No
HHS only	2,924	15.947	3	0.969	0.844	0.040	0.736	0.013	Yes (Poor fit)	No
HDDS + FIES	2924	504.793	7	0.716	0.149	0.125	<0.001	0.050	Yes (Poor fit)	No
HDDS + HHS	2924	180.099	7	0.796	0.389	0.094	<0.001	0.044	Yes (Poor fit)	No
HDDS + FIES + HHS	2924	344.192	13	0.928	0.845	0.096	<0.001	0.052	No	No

I have evaluated alternative food-security specifications because HDDS, FIES, and HHS each capture distinct dimensions of food security. HDDS reflects dietary diversity and food access, FIES measures food insecurity, and HHS indicates more severe hunger. Although combining these indicators could theoretically provide a broader measure of welfare related to resilience capacity, the fit results indicate that this combined approach does not yield improved performance with the current data. I have retained the HDDS-only MIMIC model because it was admissible and showed the best fit among the food-security specifications (CFI = 0.987, TLI = 0.935, RMSEA = 0.030, and SRMR = 0.011). Consequently, I have included HDDS in the final RCI model, while FIES and HHS serve as validation outcomes rather than components of the final MIMIC specification.

Although the retained specification fits the unweighted analytical sample well, this result is not robust to survey weighting. A survey-weighted sensitivity specification demonstrated substantially weaker model fit. Therefore, I have interpreted the retained first-stage model as an analytical-sample specification rather than a fully design-weighted population model.

5.1.2 Pillar contribution

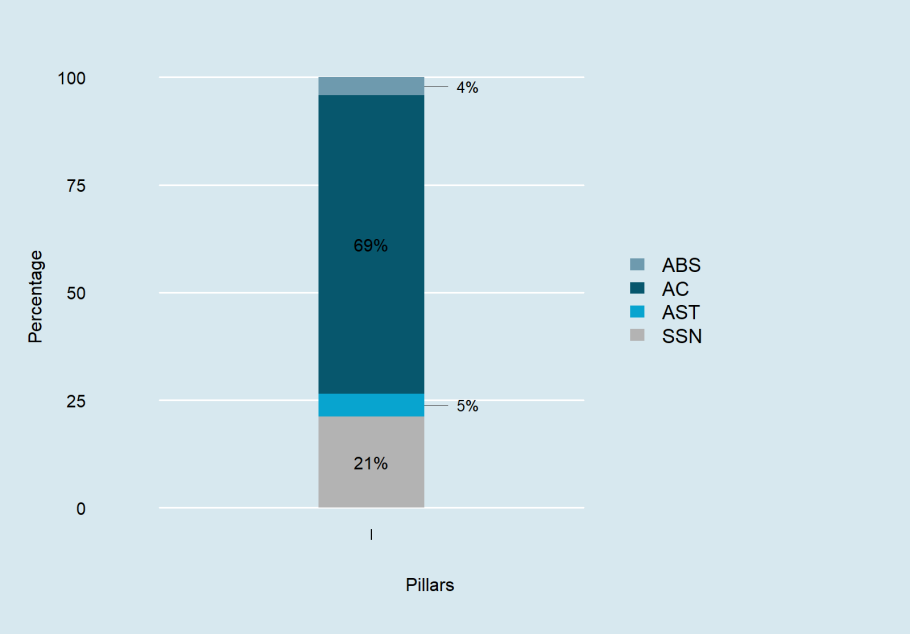
Table 3 shows the standardised scores from the four RIMA-II pillars to the latent RCI in the selected model. Adaptive Capacity has the strongest positive and statistically significant link with the RCI. Social Safety Nets have a smaller, negative, but still statistically significant link. The estimated paths from Assets and Access to Basic Services are small and not statistically significant. These coefficients show associations within the SEM and should not be seen as causal effects.

Table 3: Standardized RCI Pillar score

Pillar	Standardized coefficient	Standardized SE	p-value
Access to Basic Services (ABS)	−0.031	0.033	0.358
Assets (AST)	−0.039	0.027	0.155
Social Safety Nets (SSN)	−0.157***	0.025	<0.001
Adaptive Capacity (AC)	0.513***	0.042	<0.001

The figure below shows the percentage contribution of each RIMA-II pillar for easier understanding. It also illustrates the relative absolute sizes of the standardised pillar paths.

Figure 1: Pillar contribution (Relative absolute magnitudes of standardized pillar paths)

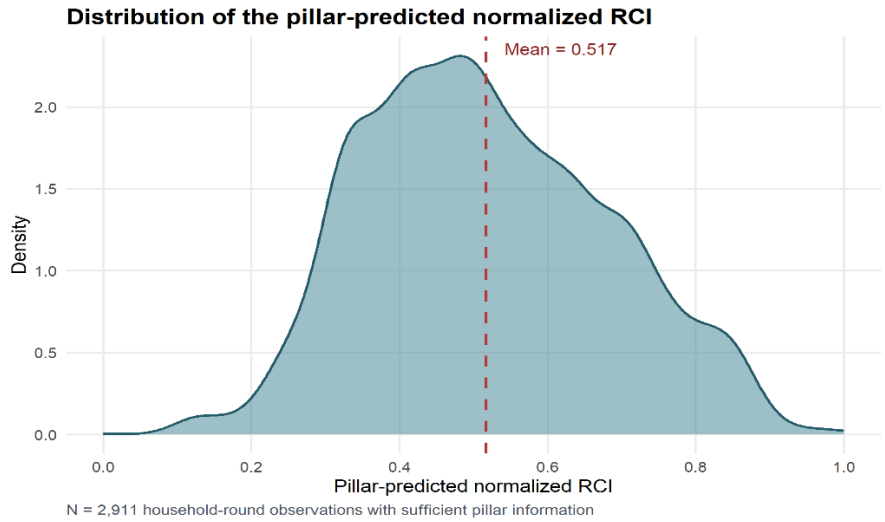


Adaptive Capacity has the highest percentage, about 69%, indicating the strongest standardised association with the latent RCI in the final SEM. Social Safety Nets account for about 21%, while Assets and Access to Basic Services have smaller shares of 5% and 4%. This figure shows relative magnitudes, not causal contributions. Since some path coefficients are negative, the percentages use the absolute values of the standardised path coefficients. The path-coefficient figure shows the sign and statistical significance.

5.1.3 Distribution of the estimated RCI

After selecting the final MIMIC specification, I extracted the predicted household-level resilience scores and rescale them to range from 0 to 1. Figure 2 shows the distribution of the estimated RCI across the entire balanced panel dataset.

Figure 2: Distribution of the pillar-predicted normalized RCI.



I obtained pillar-predicted RCI scores for 2,911 out of 2,924 household-round observations. Thirteen cases lacked sufficient pillar information after excluding HDDS from the predictions. The normalised scores had a mean of 0.517, a standard deviation of 0.164, and a median of 0.502. The first and third quartiles were 0.391 and 0.635. This distribution shows considerable variation across households and survey rounds.

5.2 Second-Stage Regression Results

Table 4 reports the second-stage regression results for the restricted sample, which includes specialised crop, specialised livestock, and mixed crop-livestock households. The dependent variable is the normalised score predicted by the retained structural equation modelling (SEM) specification. Farm-system eligibility criteria yield 2,447 household-round observations from 1,396 households. Three eligible observations do not have a pillar-predicted RCI, resulting in 2,444 observations from 1,396 households used in Equations (7-9). The models incorporate sampling weights, round fixed effects, and household-clustered HC1 standard errors.

Table 4: *Second-stage regressions using the pillar-predicted RCI*

Variable	Eq. 7 baseline	Eq. 8 + shock	Eq. 9 interaction
Intercept	0.497*** (0.009)	0.490*** (0.009)	0.493*** (0.009)
Specialized livestock	-0.031*** (0.011)	-0.029*** (0.011)	-0.032*** (0.011)
Mixed crop-livestock	0.051*** (0.010)	0.050*** (0.010)	0.045*** (0.010)
Climatic shock	-	0.044*** (0.013)	0.006 (0.021)

Specialized livestock x shock	-	-	0.029 (0.035)
Mixed crop-livestock x shock	-	-	0.057** (0.027)
Round 7	0.050*** (0.008)	0.055*** (0.008)	0.055*** (0.008)
Post-estimation test: $\beta_2 + \beta_5 > 0$	-	-	**0.102***** **(0.025)**
N	2444	2444	2444

*Notes: Entries are coefficients with household-clustered robust standard errors in parentheses. *, ** and *** indicate p < 0.10, p < 0.05 and p < 0.01, respectively. Specialized crop households are the reference group. The combined effect is calculated as $\beta_2 + \beta_5$, and its significance is based on a post-estimation linear-combination test.*

Across all model specifications (Equations 7–9), mixed crop-livestock households exhibit consistently higher normalized Resilience Capacity Index (RCI) scores relative to the reference category of specialized crop households. In the baseline additive models, the estimated differences are 0.051 (Eq. 7) and 0.050 (Eq. 8), both statistically significant at the 1% level ($p < 0.01$). Upon introducing interaction terms in Equation (9), the main effect captures the conditional difference under non-shock conditions (Shock $= 0$), remaining positive and statistically significant ($\hat{\beta}_2 = 0.045, p < 0.01$).

The interaction between mixed farming and climatic-shock exposure is positive and statistically significant ($\hat{\beta}_5 = 0.057$, SE $= 0.027$, $p = 0.033$), demonstrating that the RCI advantage of mixed systems widens under environmental stress. A post-estimation linear combination test ($\hat{\beta}_2 + \hat{\beta}_5$) confirms that the total conditional margin for mixed households under shock exposure reaches 0.102 (SE $= 0.025$, $p < 0.001$). These results of the post-estimation in table 4 indicate both a baseline premium and enhanced comparative resilience under shock conditions for mixed systems. However, these coefficients reflect conditional associations and do not imply causal mechanisms.

Conversely, specialized livestock households demonstrate significantly lower normalized RCI scores than specialized crop households in the absence of shocks ($\hat{\beta}_1 = -0.032$, SE $= 0.011$, $p = 0.004$). The interaction between livestock specialization and climatic-shock exposure is statistically insignificant ($\hat{\beta}_4 = 0.029$, $p = 0.413$). post-estimation linear-combination test of the combined conditional difference under shock exposure, calculated ($\hat{\beta}_1 + \hat{\beta}_4$) yields a point estimate near zero ($\hat{\beta} = -0.003$, $p = 0.919$), indicating no statistically discernible difference between livestock- and crop-specialized households under shock conditions.

In Equation (8), climatic-shock exposure exhibits a positive overall association with normalized RCI after controlling for farming system and survey round ($\hat{\beta} = 0.044$, SE $= 0.013$, $p < 0.001$). After the farm-system interaction terms are introduced in Equation (9), the shock coefficient represents the conditional association for the specialized crop reference group and is small and statistically insignificant (β = 0.006, p = 0.772).

In summary, mixed crop-livestock households show higher pillar-predicted RCI scores compared to specialised crop households. The positive interaction between mixed farming and shock exposure means that the difference between these groups is greater when climatic shocks

are reported. However, these findings only show conditional associations and do not prove a causal buffering effect.

5.2.3 Supplementary Validation Check

The supplementary validation check examines the relationship between the pillar-predicted RCI and related food-security and coping outcomes that were not included in the household-round score, and whether these relationships are in the expected direction. Separate weighted regressions relate the RCI to reverse-coded FIES and HHS, moderate and severe food-insecurity probabilities, and the coping-stress count, controlling for survey round and clustering standard errors at the household level.

Table 5: Supplementary concurrent validation of the pillar-predicted RCI

Outcome	Coefficient	Clustered SE	p-value
FIES (reverse coded)	0.905	0.197	< 0.001
HHS (reverse coded)	0.491	0.181	= 0.007
Moderate food insecurity probability	-0.916	0.200	< 0.001
Severe food insecurity probability	-0.535	0.183	= 0.003
Coping-stress count	0.071	0.186	= 0.703

*Notes: *, ** and *** indicate p < 0.10, p < 0.05 and p < 0.01, respectively. Positive coefficients for reverse-coded food-security measures and negative coefficients for food-insecurity outcomes support the supplementary validity of the RCI.*

The pillar-predicted RCI shows associations with four food-security measures in the expected direction. Specifically, it is positively associated with reverse-coded FIES and HHS and negatively associated with the probabilities of moderate and severe food insecurity. The coping-stress count, on the other hand, does not show a significant association with the RCI ($\beta = 0.071$, $p = 0.703$). These are concurrent, same-sample associations and should therefore be interpreted as supplementary validation rather than independent external validation.

6. Discussion

The results show that the capacity to be resilient varies between farming systems and that this varies depending on exposure to climatic shocks. The findings align with the study's hypothesis that mixed farming is linked to higher resilience than agricultural specialization, especially in the face of climatic shocks. These results are consistent with the study's expectation that mixed farming is associated with greater resilience than agricultural specialization, particularly under climatic stress. Past studies also show that there may be resilience benefits to combining crop and livestock operations (Herrero et al., 2010), and Ryschawy et al. (2012) conclude that some mixed operations are less responsive to input and output price changes than specialized operations. Seo (2010) also finds that under certain climate scenarios, integrated farms can be economically more resilient than specialized farms. Evidence that diversification can support adaptation and household food security provides further support for the observed mixed-system advantage (Mulwa and Visser, 2020). The

effectiveness of mixed farming, however, is dependent on household circumstances and enabling conditions, including markets, knowledge and infrastructure (Baker et al., 2023). In comparison, the pillar-predicted RCI scores of specialized livestock households are significantly lower than those of specialized crop households in non-shock conditions, but not in shock exposure conditions. The results, however, do not show that the difference between the two groups is significantly altered by shock exposure, as the livestock-by-shock interaction is statistically insignificant. This trend indicates that livestock ownership does not necessarily lead to the same resilience benefits as mixed crop–livestock households. It also aligns with evidence that livestock's role in shock coping is contingent on the livestock portfolio of the household and the circumstances in which livestock assets can be mobilized (Acosta et al., 2021).

The varying coefficient on climatic-shock exposure across the model specifications should not be interpreted as evidence that shocks increase household resilience. The shock coefficient in the additive model is a common conditional association for all farming systems, while in the interaction model it is the conditional association for the crop-only reference group. The interaction terms thus offer the more pertinent evidence that the association between shock exposure and resilience varies by farming system. The initially positive association may be due to a number of factors such as spatial variation in hazard exposure and adaptation experience, variation in the reporting of climatic shocks by households, and assistance or coping responses after an adverse event. The climatic hazards are highly heterogeneous in Bangladesh, and households in the areas that are often exposed to hazards may systematically differ in their experience and access to disaster-response programmes (BBS, 2016; Rahman and Lateh, 2017). Furthermore, post-shock household conditions can be a result of pre-existing resilience capacity, coping strategies and assistance received during recovery, and not necessarily the impact of the shock itself (FAO, 2018; d'Errico et al., 2018). These explanations are still hypotheses, as the data do not reveal household reporting thresholds, timing of assistance, adaptation experience or spatial variations in institutional support. The shock coefficients should thus be interpreted as conditional associations, which vary with the context, and not as causal effects.

The first-stage results indicate that Adaptive Capacity has the highest contribution to the latent resilience construct, highlighting the importance of the dimensions represented in the available data, namely livelihood flexibility, income-source diversity and household labour capacity. This trend is consistent with Mossie et al. (2024) and the emphasis placed on adaptive capacity in the RIMA-II framework (FAO, 2018). However, the factors that contribute to resilience are situation specific. For instance, Tasnim et al. (2025) find that Adaptive Capacity has a positive but statistically insignificant effect in rural Bangladesh, whereas Access to Basic Services and some asset groups have larger effects. This difference is an indication that the estimated pillar contributions are dependent on household characteristics, indicator selection and model specification (Ngesa et al., 2021). The small contribution of Assets and Access to Basic Services in the current model should not be interpreted as evidence that these resources are generally unimportant. Likewise, the negative relationship for Social Safety Nets does not imply that social safety nets make households less resilient, but rather that they are targeted to more vulnerable households. The results of the supplementary validations generally confirm

the concurrent validity of the predicted RCI, which is consistently associated with food-security measures based on dietary and experience. This aligns with the recommendations that resilience measures should be assessed based on measurable welfare outcomes (Ansah et al., 2019; Upton et al., 2022). However, the lack of a clear relationship with the coping-stress count suggests that the validation evidence is supportive but not consistent for all outcome measures.

The study contributes to the literature by comparing multidimensional resilience capacity between crop-only, livestock-only and mixed crop–livestock households and by testing whether these differences change with reported exposure to climatic shocks. Past studies in Bangladesh have shown the significance of farm and livelihood diversification for food security and weather shocks (Islam et al., 2018; Matsuura-Kannari et al., 2023), and other studies have explored the factors influencing household resilience using the RIMA framework (Tasnim et al., 2025). The present analysis links these areas by identifying farming-system types and their relationship with a multidimensional resilience measure under various shock scenarios. The findings indicate that policy interventions should not be limited to livestock ownership or to engaging in more than one agricultural activity, but to the conditions that enable households to reap benefits from integrated production. Better veterinary services, access to feed markets and climate-information services could help households make better use of mixed farming, but the observational results do not prove the causal impact of such services.

These conclusions are subject to several limitations. The two-round panel dataset is a relatively short timeframe and cannot explore long-term resilience trajectories, recovery processes or adaptation to repeated climatic shocks. Another restriction is that panel attrition is considered, meaning that only households that are observed in both survey rounds are included in the analysis, which excludes a large number of unmatched observations. This can lead to a less representative analytical sample if the households that are dropped from the balanced panel are systematically different from those that are kept. It also does not determine if there were differences in resilience prior to the adoption of the current farming systems. The binary farm-system classifications do not reflect production scale, management intensity, herd composition, profitability or the level of integration between crop and livestock enterprises. Likewise, the composite shock measure aggregates various climatic hazards without considering the timing, duration, location or severity of the events, and the estimates are average relationships across events of varying characteristics. The RCI measurement model is based on the Household Dietary Diversity Score, which reflects only one aspect of food security, but the supplementary validation results offer more general support for the index. Furthermore, the first-stage model retained is estimated without survey weights, since the weighted version of the model yielded significantly poorer model fit; the pillar relationships should thus be interpreted as characteristics of the analytical sample rather than as fully population-representative estimates. Lastly, pooled regressions cannot remove household and spatial attributes that could affect both farming-system classification and resilience. Household fixed-effects estimation was not retained because the two-round structure would only identify the effects of farming systems from households that changed categories, and this may be partly due to temporary activity or reporting differences. The estimated relationships should thus be interpreted as associations and not as causal effects.

7. Conclusion

This thesis explored the resilience capacity of households in different farm-system typologies in rural Bangladesh and how their differences change as a function of reported exposure to climatic shocks. A latent Resilience Capacity Index (RCI) was developed based on a two-round balanced Data in Emergencies (DIEM) panel dataset, using the RIMA-II framework. Farm-system classifications, climatic-shock exposure were not directly mechanically linked to RCI construction, avoiding direct mechanical overlap with the second-stage analysis. But this separation does not rule out endogeneity due to household self-selection or unobserved characteristics.

The pillar-predicted RCI scores are significantly higher for mixed crop-livestock households than for specialized crop households in both non-shock and shock scenarios. The mixed-farming-by-shock interaction is positive and statistically significant, suggesting that this difference is greater under reported shock exposure, and the post-estimation test of $\beta_2 + \beta_5$ confirms the higher mixed-system RCI under shock conditions. In contrast, specialized livestock households have lower RCI scores than specialized crop households in non-shock conditions, but there is no statistically significant difference in RCI scores between the two types of households in shock exposure conditions. These findings are conditional associations and not causal effects of farm-system choice.

The positive mixed-farming coefficient and mixed-farming-by-shock interaction indicate the potential benefits of targeting households that practice both crop and livestock farming, and the strong relationship between Adaptive Capacity and the RCI points to the importance of livelihood flexibility and income-source diversity from a policy perspective. The analysis does not specify what interventions would lead to these results, and the policy implications should be interpreted with caution. Future studies should incorporate longer panels wave, more precise farm-system indicators, more comprehensive food-security indicators, and more detailed climatic-shock information to explore resilience pathways and enhance causal interpretation.

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Popular Science Summary

Mixed crop–livestock households in rural Bangladesh are more resilient to climatic shocks than crop-only households. This finding is important because floods, droughts and cyclones can affect farming, income and food security, and households may vary in their capacity to cope with these events.

The question of this thesis is whether the organisation of farming activities is related to the coping ability of the households. The study compares households specializing in crops, specializing in livestock, and mixed households. It relies on two cycles of FAO's Data in Emergencies Monitoring surveys, conducted over time with 1,462 households. Resilience is considered in a broad sense, not only in terms of food security, but also access to basic services, assets, social safety nets and adaptive capacity.

Results indicate that mixed crop–livestock households are more resilient than crop-only households in both non-shock and shock conditions, and that the gap between the two increases among households that experienced climatic shocks. Livestock-only households are less resilient than crop-only households in the absence of a shock, while the study reveals no significant difference between the two groups when a shock is reported.

A possible explanation is that the integration of crops and livestock provides households with greater options to utilize their resources and generate food and income in response to change. The study does not, however, demonstrate that mixed farming per se leads to higher resilience. The results are associations, and the advantages of mixed farming can vary due to market, knowledge, infrastructure and support services.

The results can be used by policy makers and rural-development programmes to pinpoint the conditions that enable households to reap the benefits of integrated farming, such as access to veterinary services, feed markets and climate information.

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