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Climate-induced educational disruption: Evidence on multidimensional assessment from the Haor Region of North-Eastern Bangladesh

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Abstract: Educational disruption due to a changing climate remains underexplored in flood-prone regions, particularly where communities face additional socioeconomic stress. This study assesses educational vulnerability in Tahirpur, a flash-flood-prone area of Sunamganj, Bangladesh. A total of 304 respondents affiliated with 24 educational institutions were surveyed to assess vulnerability across three dimensions and adaptive capacity across four categories. The analysis employed Spearman's rank correlation and the Kruskal–Wallis test, followed by Bonferroni-adjusted Mann–Whitney U post hoc comparisons. A significant inverse relationship was identified between overall adaptive capacity and overall vulnerability ($\rho = -0.928$, $p < .001$). Environmental vulnerability showed the strongest decline with increasing adaptive capacity ($\rho = -0.857$), followed by sociocultural vulnerability ($\rho = -0.785$), whereas the relationship with economic vulnerability was comparatively weaker ($\rho = -0.546$). The findings indicate that higher institutional adaptive capacity was associated with lower vulnerability across all three dimensions. Furthermore, routine maintenance, infrastructure readiness, environmental hygiene, disaster training, planning integration, and information systems were the adaptive capacity indicators most strongly associated with overall institutional adaptive capacity. These findings demonstrate that educational disruption is a complex issue that extends beyond a simple relationship with poverty and disaster exposure in climate-vulnerable settings. The evidence contributes to the development of a climate-responsive institutional framework for integrating education into disaster risk reduction and climate adaptation policies through improved planning, financing, and community-linked preparedness systems.

Keywords: Floods; Educational Disruption; Haor Region; Vulnerability; Adaptive Capacity.

1.0 Introduction

Bangladesh's north-eastern Sylhet region, situated downstream of the Meghalaya Hills in India, receives high monsoon rainfall of around 2,300 mm annually, while its low-lying topography and hydro-morphological conditions create recurrent exposure to floods and flash floods (Berndt, 2022; Hossain et al., 2020; Rahman et al., 2025). For instance, in 2022, extensive rainfall triggered flooding that affected an estimated 7.2 million people in the region and was reported as one of the most severe natural disasters in the history of the greater Sylhet region. Subsequently, from May to June 2024, another major flood affected more than 2 million people in the region (Das, 2022; UNICEF, 2024a). Within this vulnerable landscape, Sunamganj district is among the most flood- and flash-flood-prone areas, encompassing more than 133 haors, defined as bowl-shaped, basin-like tectonic depressions, which cover almost 43% of the district's total land area (Akter et al., 2023a; Akter et al., 2023b). The topography of Sunamganj, together with rapid upstream runoff from the Meghalaya Hills, generates flash floods that differ from seasonal floods by arriving suddenly and receding rapidly while leaving lasting economic and social impacts (Dey et al., 2021). In addition to these topographic and climatic characteristics, limited capital development and resource constraints have contributed to making Sunamganj one of the poorest districts in the country (Hoq et al., 2021; Mia, 2022).

Among the sectors affected by these recurrent floods and flash floods, the education system represents a particularly underexamined dimension of climate vulnerability. In Bangladesh, climate-induced educational vulnerability is increasingly recognised as a major challenge in flood-prone regions, although the nature and severity of flood-related impacts on education vary considerably across geographical contexts (Hoque et al., 2024). In coastal areas, educational disruptions are often associated with cyclones, storm surges, and salinity intrusion, which typically result in temporary school closures and damage to educational facilities (Cesti et al., 2026). In riverine char regions, riverbank erosion and displacement are the primary drivers of educational vulnerability, forcing children to relocate frequently and interrupting educational continuity (Hossain et al., 2025).

In contrast, the haor region of Sunamganj experiences a distinct form of educational vulnerability due to recurrent flash floods and prolonged seasonal inundation. Unlike other flood-prone regions, where disruptions are often episodic, flash floods in Sunamganj occur almost annually and can isolate communities for extended periods by submerging roads, schools, and communication networks (Mia, 2022; Salam et al., 2026). Moreover, educational vulnerability in Sunamganj is closely linked to livelihood insecurity. The regional economy largely depends on a single annual Boro rice harvest, and flood-induced crop losses frequently reduce household income, compelling children to engage in income-generating activities or domestic responsibilities rather than attend school (Farid et al., 2021; Islam et al., 2014; Mia, 2022; Salam et al., 2026). This economic dimension of educational vulnerability may be more pronounced in Sunamganj than in many other parts of Bangladesh where livelihoods are relatively diversified. For instance, one study found that 42.2% of respondents had no formal or institutional education, while 58.9% experienced income loss during flash floods (Dey et al., 2021).

Sunamganj district also records relatively high school dropout rates, with flooding and associated socioeconomic challenges contributing to educational discontinuity (Dewan, 2017). In 2021, the primary school dropout rate in the district reached 44%, compared with a national average of 40%, while the secondary school dropout rate also remained comparatively high (Bhuiyan et al., 2024; Suvra, 2021; UNICEF, 2024a). Floods and flash floods frequently damage educational infrastructure, disrupt school activities, and undermine students' ability and motivation to continue their studies (Farid et al., 2021). During the 2022 floods, more than 873 educational institutions, mostly government primary schools, were closed across Sylhet and Sunamganj (NAWG, 2022). Furthermore, in the aftermath of flooding, damaged infrastructure, inadequate water and sanitation facilities, and family displacement can further impede children's access to educational institutions (Tasnim, 2022). Community responses following floods are often reactive because households must first prioritise food, income, and shelter. Flood damage reduces agricultural income, disrupts fishing and wage labour, and increases household debt and social stress (Abedin & Khatun, 2019; Dey et al., 2021; Hoq et al., 2021). Under such circumstances, households may prioritise immediate survival strategies over continued investment in education. Boys may be withdrawn from school to participate in income-generating activities, such as fishing and seasonal labour, while girls may face pressure to marry early as a means of reducing household expenses and perceived social risks (Alston et al., 2014; Farid et al., 2021; Sarker et al., 2019).

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These patterns suggest that flood exposure alone does not fully explain educational vulnerability. At the same time, educational disruption should not be treated simply as an outcome of livelihood vulnerability. Rather, it can be understood as a continuing process shaped by three interconnected conditions: environmental exposure, sociocultural pressures, and economic fragility (Gull et al., 2024; Lassa et al., 2023). Understanding this process requires a multidimensional vulnerability approach that distinguishes environmental, sociocultural, and economic components (ECLAC, 2022; IPCC, 2022; Reisinger et al., 2020). The environmental dimension encompasses flood exposure, infrastructure damage, waterlogging, and health risks. The sociocultural dimension includes child labour, early marriage, seasonal absenteeism, and attitudes towards schooling. The economic dimension encompasses household and institutional financial constraints that affect preparedness, recovery, and educational continuity (Lassa et al., 2023).

Existing literature on the haor region has generally assessed these factors separately. Some studies focus primarily on flood impacts and educational infrastructure, whereas others examine social consequences such as livelihood loss, school dropout, and household coping practices. Few studies, however, integrate environmental, sociocultural, and economic dimensions within a single assessment of educational vulnerability at the institutional level. This represents an important empirical gap that the present study addresses.

A further gap concerns whether and how institutional adaptive capacity is associated with educational vulnerability in flood-affected areas. Although previous studies have discussed this relationship conceptually, few have empirically examined it using institution-level data in a recurrently flood-affected setting (Adger, 2003; Varchetta, 2019). Examining this relationship is important for understanding whether and how educational institutions can reduce vulnerability through practical preparedness and adaptive measures. This study therefore addresses these gaps by assessing climate-induced educational vulnerability in Sunamganj district through a multidimensional framework. It considers environmental, sociocultural, and economic dimensions because previous research has largely examined these dimensions independently, despite the interconnected pathways through which floods affect education. The study has two objectives: (1) to assess institutional adaptive capacity and multidimensional educational vulnerability; and (2) to examine whether higher institutional adaptive capacity is associated with lower educational vulnerability.

2.0 Study Area

The Haor basin of north-eastern Bangladesh, a bowl-shaped floodplain depression spanning seven districts, was selected because it experiences pre-monsoon flash floods generated by runoff from the Meghalaya and Assam hills almost annually. In addition, near-total dependence on a single annual Boro rice crop means that agricultural losses and household income shocks often coincide with the academic year (Baishakhy et al., 2023). Within the basin, Tahirpur sub-district of Sunamganj was selected as one of the most exposed upazilas because of its recurrent flash-flood impacts and embankment failures around Tanguar Haor. The area has also been selected on similar grounds in previous flash-flood research in the region (Baishakhy et al., 2023). The impacts of the 2022 flash floods on educational institutions across Sylhet and Sunamganj further demonstrate the district's relevance as a setting for examining climate-induced educational disruption (NAWG, 2022).

The study was conducted in four unions, Dokkhin Borodol, Uttar Sreepur, Balijuri, and Tahirpur Sadar, within Tahirpur sub-district (25°01′–25°12′ N; 91°02′–91°19′ E), Sunamganj district [Figure 1]. A total of 24 educational institutions were included in the study. The unions and educational institutions were selected based on expert consultation involving academics, development practitioners, and local government officials over a one-month period. Flood and flash-flood vulnerability, accessibility, and remoteness were also considered in the selection of the unions and educational institutions. The selected institutions comprised primary schools, high schools, madrasas (Islamic religious schools), and degree colleges, as identified from records provided by the Upazila Primary Education Department (UPED) and the Upazila Education Department (UED).

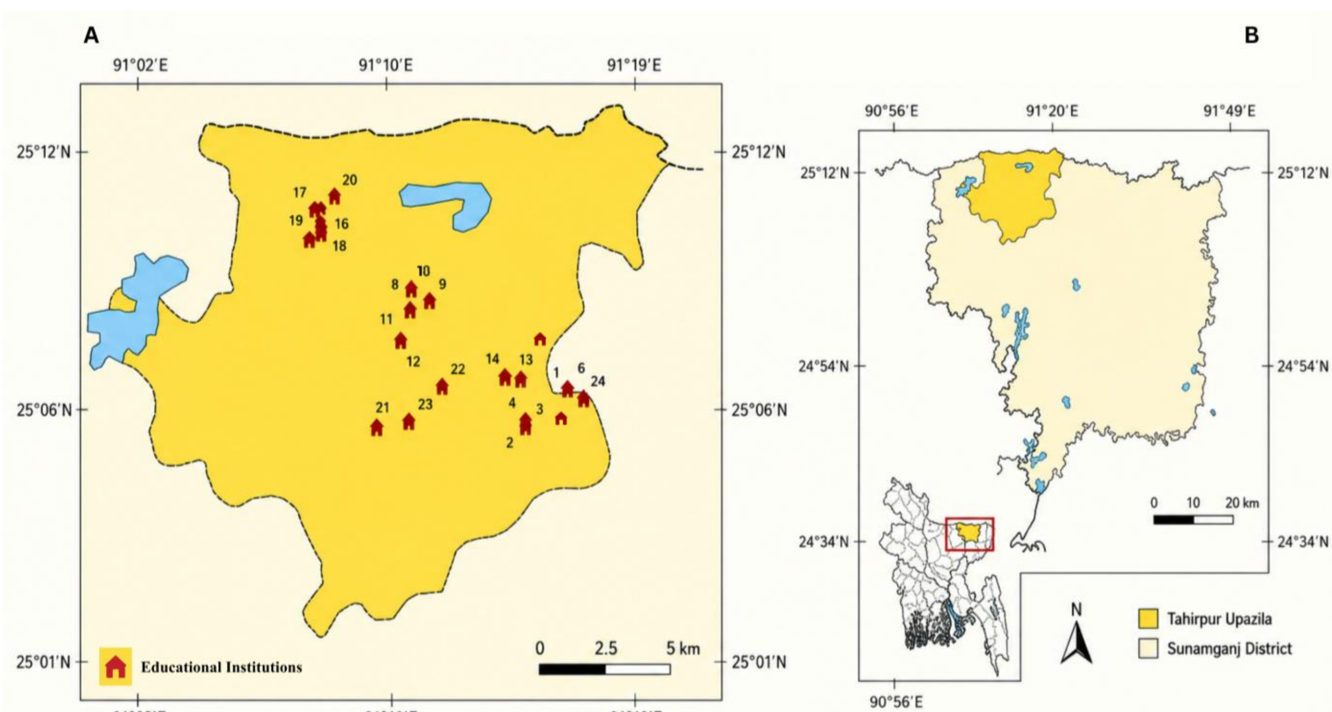

Figure 1: (A) Study area showing the locations of selected educational institutions and (B) Tahirpur Sub-district within Sunamganj District (Source: Authors, 2026).

3.0 Materials and Methodology

3.1 Materials

Tahirpur sub-district has a total population of 22,48,641 (BBS, 2023). The four unions selected for this study have a combined population of 1,09,509 (N). During the initial scoping phase, caregivers, academics, administrative staff, and local community representatives from the study area were interviewed using a semi-structured questionnaire developed and reviewed during the initial phase of the study. Informed consent was obtained from all participants prior to the interviews. Following the scoping study, a questionnaire survey was conducted among residents of the selected unions.

$$n = \frac{N}{1+N(e^2)} \text{.................................... } \textit{Eq. 1}$$

Using Yamane's formula (Eq. 1), with a 95% confidence level, the initial sample size was estimated at approximately 400 respondents. However, because the total eligible population of caregivers and staff across the 24 selected educational institutions was unavailable, this estimate was based on the population of the four selected unions and was treated as an initial target rather than as a probability-based sample-size requirement.

The study population comprised caregivers of enrolled students and teaching or administrative staff affiliated with the 24 selected educational institutions. As consolidated enrolment and staff registers were unavailable, the sampling frame was constructed at the institutional level. Respondents were selected by category using non-proportional allocation based on institutional size, respondent availability, and accessibility. Accordingly, the achieved sample was non-probability based, and the inferential analyses are interpreted as describing associations within the surveyed sample rather than providing population-representative estimates. A total of 304 respondents provided complete responses, with no recorded refusals or questionnaires excluded because of incomplete responses. However, the total number of individuals approached was not systematically documented.

The achieved sample was lower than the initial target of 400 because the initial estimate was based on the total population of the four selected unions, whereas the survey was restricted to the accessible population associated with the selected educational institutions. Only marginal distributions by respondent category, union, and institution type are reported because the small and uneven cell sizes limit the meaningful interpretation of cross-tabulations. The distribution of the 24 educational institutions is provided in Supplementary Table S1. All participants were informed of the research objectives before participation.

3.2 Data processing and analysis

The study used quantitative survey data. Respondents rated Likert-scale items, and the responses were coded on a 1–5 scale for analysis (Jamieson, 2004). The Sendai Framework for Disaster Risk Reduction and the IPCC climate risk framework guided the conceptualisation of vulnerability and adaptive capacity (ECLAC, 2022; Reisinger et al., 2020; UNDRR, 2015). Vulnerability was assessed using environmental, sociocultural, and economic indicators, while adaptive capacity was assessed using physical, human, institutional, and external relationship factors (Tables 1–2).

The indicators were developed based on established vulnerability and adaptive capacity frameworks. Vulnerability indicators covered environmental, sociocultural, and economic dimensions, following the framework proposed by Hahn et al. (2009). Adaptive capacity indicators were guided by the Comprehensive School Safety Framework and other established literature (Global Alliance for Disaster Risk Reduction & Resilience in the Education Sector [GADRRRES], 2022; Shah et al., 2020a; Adger, 2003; IPCC, 2022). The indicators were further refined through expert consultation to ensure their contextual relevance and clarity for educational institutions in the Haor region. The final instrument comprised 24 vulnerability sub-indicators and 48 adaptive capacity sub-indicators, with equal weighting applied to the sub-indicators (OECD, 2008).

Table 1: Vulnerability indicators: Sub-indicators were rated on a 5-point Likert scale. Likelihood ranged from 1 (less likely) to 5 (most likely), and severity from 1 (negligible) to 5 (severe). Vulnerability was calculated as likelihood × severity (1–25) and standardised to a 1–5 scale.

Cluster	Sub-Indicators
Environmental Indicators	School closure due to flash flood
	Unavailability of teachers/academics
	Immobility due to waterlogging
	Damage to learning materials due to extreme events
	Postponing exams and reducing the syllabus due to extreme events
	Health risk due to extreme weather
	Infrastructural damage to institutions due to extreme events
Socio- Cultural Indicators	Child labor-related student drop-out.
	Child marriage-related student drop-out.
	Low attendance in class due to the poor transport system
	Low attendance in class due to remoteness
	Low attendance in class during the agriculture season
	Low attendance due to the lack of motivation of guardians and students
	Low attendance due to the lack of motivation of teachers
	Low attendance due to poor school environment and service delivery
	Low attendance in class due to the absence of teachers
Economic Indicators	Poverty-related student drop-out
	Lack of the guardian's motivation due to limited livelihood
	Lack of motivation among students due to limited job opportunities
	Guardians often use their child as a source of income.
	Unable to retrieve damaged learning materials
	No funds for schools for repairing and reconstruction after a disaster
	Lack of funds for disaster preparedness
	Lack of guardian's emergency fund for education

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Table 2: Indicators to estimate adaptive capacity

Indicators	Sub-indicators	Factors
Physical condition	School building as infrastructure	Regular checks on school buildings **(SB1)** Possible extent of infrastructural damage sustained **(SB2)** Floodproofing initiative/structure/activities **(SB3)** Promptness in rebuilding damaged infrastructure **(SB4)**
	Facilities and equipment	Regularly check on facilities and equipment. **(FE1)** Floodproofing equipment **(FE2)** Emergency supplies **(FE3)** Alternative transportation facilities and support (etc., boat) **(FE4)**
	Hygienic and environmental conditions	Environmental protection literacy **(HE1)** Regular checks on hygiene maintenance **(HE2)** Recovery after using it as a flood shelter **(HE3)** Separate washroom facilities **(HE4)**
Human resources	Teachers and staff	Possibility of Being Affected by Disaster **(TS1)** Disaster training program for teachers and staff **(TS2)** Sharing of the disaster preparedness plan for teachers and staff **(TS3)** Access to DRR guide/manual **(TS4)**
	Students	Possibility of Being Affected by the disaster **(ST1)** Knowledge about disasters (particularly floods and flash floods) **(ST2)** Disaster training program by teachers and staff **(ST3)** Participation in disaster programs/drills/training **(ST4)**
	Caregivers (Parents/guardians)	Parent-teacher meeting **(PG1)** Disaster training program/workshop for parents **(PG2)** School–home emergency notification **(PG3)** Sharing of the disaster preparedness plan for parents **(PG4)**
Institutional issues	Planning	Incorporation of disaster components into school planning **(PL1)** Incorporation of disaster components into the school syllabus **(PL2)** Preparedness and emergency management plan **(PL3)** Recovery management plan **(PL4)**
	Management and governance	Early warning system at the school level **(MG1)** Disaster information **(MG2)** Disaster committees **(MG3)** Training/drills for disaster committees **(MG4)**
	Allocation of funds and budget	Budget allocated for disaster training activities. **(AF1)** Budget allocated for disaster preparedness and response. **(AF2)** Budget allocated for renovation/repair/rebuilding after a disaster. **(AF3)** The budget allocated for monitoring. **(AF4)**
External relationship	Collaboration	Meeting with district UEO **(CO1)** Meeting with the local people's committee **(CO2)** Early warning from the local government **(CO3)** Collaboration with the local government **(CO4)**
	School and community interaction	Multipurpose use of the school (as a flood shelter) **(SC1)** Participation of the school in disaster activities held by the local community **(SC2)** Support from the local community **(SC3)** School involvement in the disaster management plan of the local community **(SC4)**
	Fund mobilization	Funds from the local government **(MF1)** Funds from the local community **(MF2)** Funds from other organizations **(MF3)** Shifting budget **(MF4)**

Note: Adapted and Modified from Adger (2003) and IPCC (2022). All sub-indicators rated on a 5-point Likert scale (Very low = 1 to Very high = 5).

Vulnerability was assessed across environmental, sociocultural, and economic dimensions, while adaptive capacity was measured across physical, human resource, institutional, and external relationship dimensions. Climate risk was conceptualised as the interaction of hazard, exposure, and vulnerability, with adaptive capacity potentially reducing vulnerability and educational disruption. The analysis therefore examined the association between adaptive capacity and educational vulnerability rather than calculating a separate risk score. Figure 2 illustrates the nexus among hazards, exposure, adaptive capacity, educational impacts, and the key concepts examined in this study.

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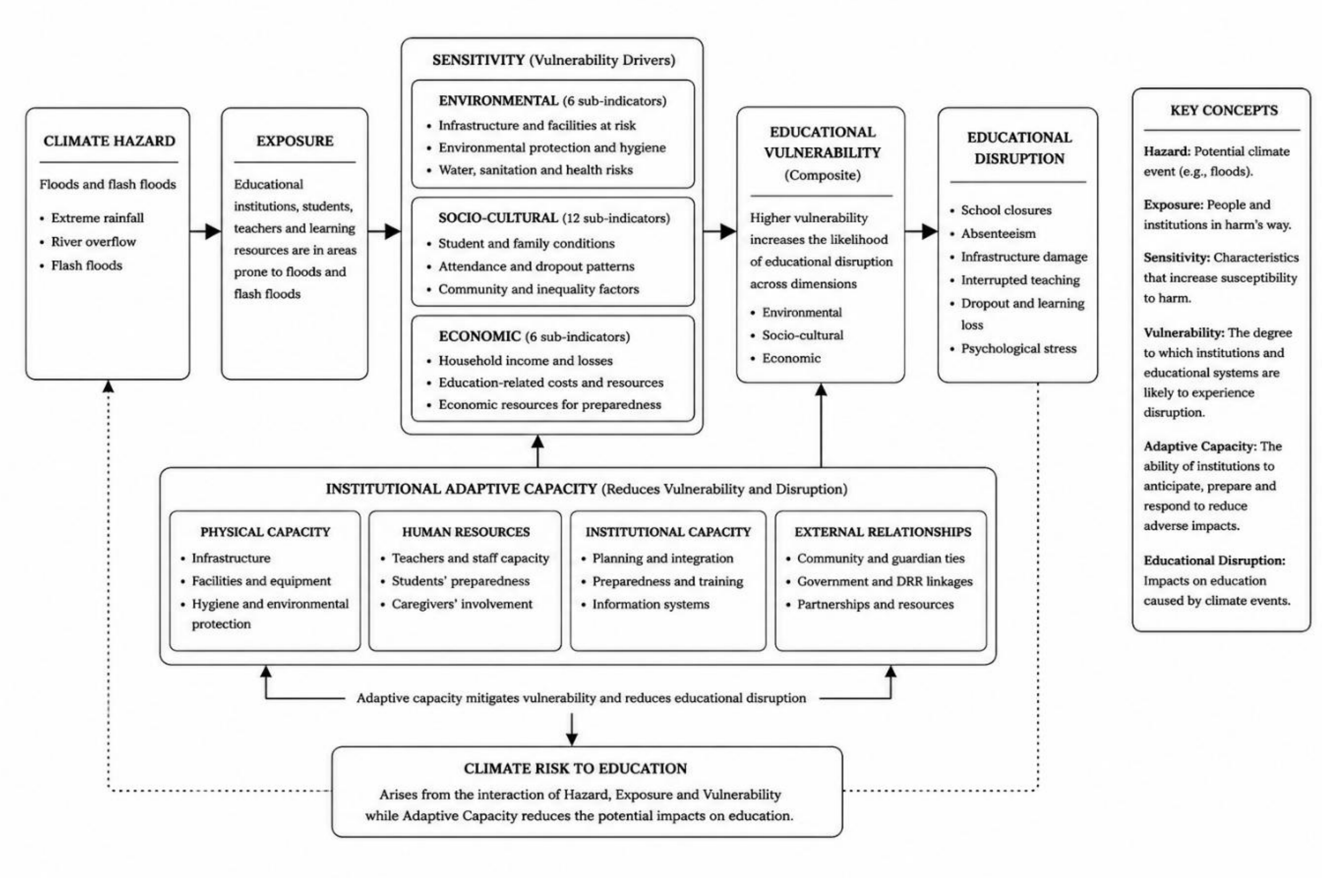

Figure 2: Conceptual framework and key indicators of this study (Source: Authors, 2026)

Given the ordinal nature of the data and the absence of normality assumptions, non-parametric statistical techniques were applied throughout the analysis (Jamieson, 2004; Mızrak & Aslan, 2020; Şermet Kaya & Erdoğan, 2025; Vasilopoulos, 2019). Cronbach's alpha was used to assess the internal consistency and reliability of the adaptive capacity (AC) and vulnerability sub-indicators, yielding $\alpha = 0.95$ for the adaptive capacity sub-indicators and $\alpha = 0.88$ for the vulnerability sub-indicators, indicating high internal consistency. Subsequently, the relationships between adaptive capacity and vulnerability dimensions were examined using Spearman's rank-order correlation (ρ) (Eq. 2), which assesses monotonic associations and is appropriate for ordinal data (Spearman, 1904). In Eq. 2, ρ represents Spearman's rank correlation coefficient, d_i is the difference between the ranks of each pair of observations, and n is the number of paired observations in the dataset.

$$\rho = \frac{6\sum d_i^2}{n(n^2-1)} \text{........................ Eq. 2}$$

As respondents were nested within 24 educational institutions, institutional clustering was assessed using intraclass correlation coefficients (ICCs). Respondent-level observations ($n = 304$) were retained, and the robustness of the Spearman correlations was assessed using an institution-level cluster bootstrap with 10,000 replications.

To assess the contribution of individual adaptive capacity indicators while avoiding part–whole correlation, corrected item–total correlations were calculated. For each of the 48 adaptive capacity indicators, the overall adaptive capacity composite was recalculated after excluding the focal indicator, and Spearman's rank-order correlation was then estimated between the focal indicator and the corresponding 47-item corrected composite. This procedure removes the focal indicator's direct mathematical contribution to the composite with which it is correlated. Higher corrected coefficients indicate stronger consistency between an individual indicator and the remaining adaptive capacity construct. Figure 3 summarises this methodological process.

To further explore differences across levels of institutional capacity, adaptive capacity scores were grouped into tertiles representing low, medium, and high capacity (see Supplementary Table S2). These boundaries are sample-relative and do not represent absolute benchmarks of institutional capacity. Tertiles were used solely to illustrate the vulnerability gradient across capacity levels, while adaptive capacity was retained as a continuous variable in the Spearman analyses; therefore, no information was discarded from the inferential analyses. Differences in vulnerability across the three groups were tested using the Kruskal–Wallis H test for comparing more than two independent groups (Guo et al., 2013), followed by Bonferroni-adjusted Mann–Whitney U post hoc comparisons. Statistical significance was evaluated using Eq. 3 at conventional thresholds ($p < .05$, $p < .01$, and $p < .001$). In Eq. 3, H is the Kruskal–Wallis statistic, R_i is the sum of ranks in the ith group, n_i is the number of observations in the ith group, and N is the total number of observations across all groups.

$$H = \left[\frac{12}{N(N+1)}\sum\frac{R_i^2}{n_i}\right] - 3(N+1) \text{................................} \textit{Eq. 3}$$

Scatterplots were used to illustrate the relationships between adaptive capacity and vulnerability. OLS trend lines were added solely to aid visual interpretation, while statistical testing was conducted using non-parametric methods. Bar charts present mean values with ±1 standard error (SE) to illustrate variation across adaptive capacity groups.

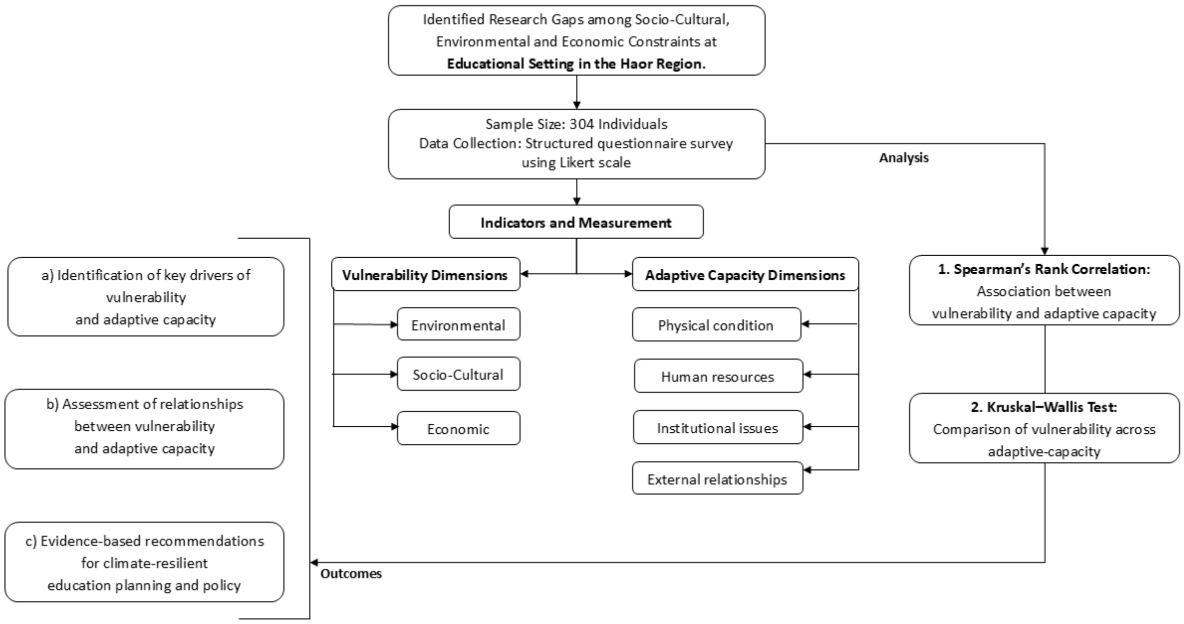

Figure 3: Methodological framework of the study (Source: Authors, 2026).

4 Results

4.1 Demographic profile

The demographic characteristics of the study participants are presented in Table 3. Of the 304 respondents, 57.9% were female and 42.1% were male. In terms of respondent type, the majority were caregivers (58.6%), while 41.4% were teachers or academic staff affiliated with the selected educational institutions. Most respondents were aged 21–40 years (63.0%). Monthly income varied among respondents. Approximately 40.46% reported monthly earnings below BDT 12,500, 20.7% reported income between BDT 12,500 and 21,500, and 39.47% reported earnings above BDT 21,500. Respondents were drawn from four unions, with the largest proportion from Dokkhin Borodol (44.1%), followed by Uttar Sreepur (31.3%), Balijuri (22.7%), and Tahirpur Sadar (2.0%). By institution type, most respondents were affiliated with primary schools (68.1%), followed by high schools (21.1%), madrasas (7.9%), and degree colleges (3.0%). This distribution reflects the predominance of primary-level institutions in the study area. Supplementary Table S3 provides the frequency distribution by union and institution type.

Table 3: Demographic characteristics of the study respondents (n = 304)

Category	% (n= number out of total population)
Gender	
Male	42.1% (n=128)
Female	57.9% (n=176)
Type of respondent	
Caregivers	58.6% (n=178)
Teachers/ Academics	41.4% (n=126)
Age	
21-40	63% (n=192)
41-60	35% (n=106)
61-80	2% (n=6)
Monthly income	
Below 12500 BDT	40.46% (n= 123)
Between 12500 and 21500 BDT	20.7% (n= 61)
Above 21500 BDT	39.47% (n= 120)
Union	
Dokkhin Borodol	44.1% (n = 134)
Uttar Sreepur	31.3% (n = 95)
Balijuri	22.7% (n = 69)
Tahirpur Sadar	2.0% (n = 6)
Institution type	
Primary school	68.1% (n = 207)
High school	21.1% (n = 64)
Madrasa	7.9% (n = 24)
Degree college	3.0% (n = 9)

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4.2 Association between adaptive capacity and vulnerability
4.2.1 Indicators for measuring adaptive capacity

Table 4 presents the corrected item–total correlations for the 48 adaptive capacity indicators. The strongest associations were observed for regular facility maintenance (FE1: ρ = 0.810), school inspections (SB1: ρ = 0.766), and environmental literacy (HE1: ρ = 0.740). Disaster training (TS2: ρ = 0.704), integration into planning (PL1: ρ = 0.698; PL2: ρ = 0.692), and disaster information systems (MG2: ρ = 0.690) also showed relatively strong associations. External linkages included collaboration with local government (CO4: ρ = 0.622) and early warning systems (CO3: ρ = 0.603). Weaker associations were observed for financial indicators, including the preparedness budget (AF2: ρ = 0.290), financial monitoring (AF4: ρ = 0.241), and external funding (MF3: ρ = 0.208). Changes in budget allocation (MF4: ρ = 0.112) and disaster impacts on students (TS1: ρ = −0.004) showed negligible associations, whereas disaster impacts on staff (TS1: ρ = −0.121) showed a weak negative association. Overall, routine maintenance, environmental preparedness, training, planning, information systems, and external linkages showed stronger associations with adaptive capacity than financial indicators. Corresponding p-values are provided in Supplementary Table S4.

Table 4: Item–total Spearman correlations for adaptive capacity indicators (n = 304)

AC Dimension	Code	Corrected ρ	Sig.	AC Dimension	Code	Corrected ρ	Sig.
Physical Condition	SB1	+0.766	***	Institutional Issues	PL1	+0.698	***
	SB2	+0.528	***		PL2	+0.692	***
	SB3	+0.532	***		PL3	+0.532	***
	SB4	+0.402	***		PL4	+0.599	***
	FE1	+0.810	***		MG1	+0.650	***
	FE2	+0.677	***		MG2	+0.690	***
	FE3	+0.527	***		MG3	+0.659	***
	FE4	+0.472	***		MG4	+0.590	***
	HE1	+0.740	***		AF1	+0.371	***
	HE2	+0.676	***		AF2	+0.290	***
	HE3	+0.631	***		AF3	+0.324	***
	HE4	+0.505	***		AF4	+0.241	***
Human Resources	TS1	−0.121	*	External Relationships	CO1	+0.504	***
	TS2	+0.704	***		CO2	+0.346	***
	TS3	+0.545	***		CO3	+0.603	***
	TS4	+0.355	***		CO4	+0.622	***
	ST1	−0.004	ns		SC1	+0.560	***
	ST2	+0.599	***		SC2	+0.589	***
	ST3	+0.584	***		SC3	+0.404	***
	ST4	+0.372	***		SC4	+0.442	***
	PG1	+0.358	***		MF1	+0.305	***
	PG2	+0.505	***		MF2	+0.447	***
	PG3	+0.604	***		MF3	+0.208	***
	PG4	+0.530	***		MF4	+0.112	ns

Note. For each indicator, the adaptive capacity composite was recalculated after excluding the focal indicator; Spearman's ρ therefore represents the corrected item–total association. *** p < .001; * p < .05; ns = not significant (p ≥ .05). Vulnerability assessment

After identifying the adaptive capacity indicators, the analysis examined whether higher adaptive capacity was associated with lower vulnerability. Figure 4 illustrates the relationships between overall adaptive capacity (AC) and environmental, sociocultural, economic, and overall vulnerability based on 304 responses.

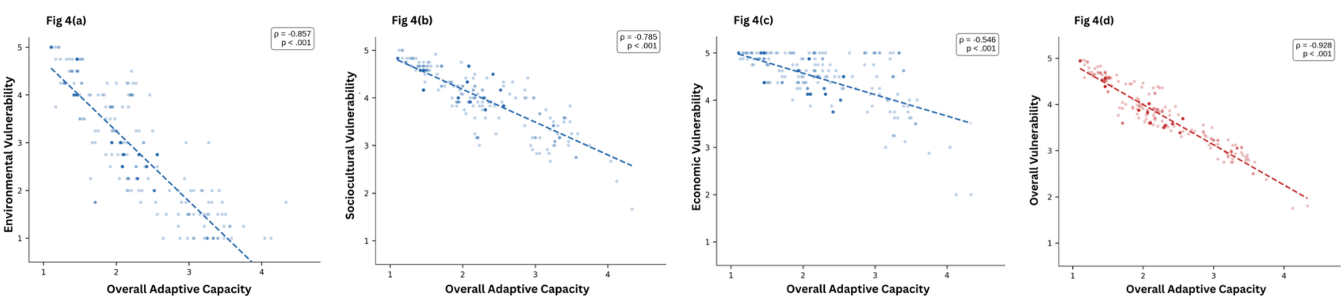

Figure 4: Scatterplots of overall adaptive capacity versus vulnerability dimensions (n = 304). Each plot shows the Spearman rank-order correlation (ρ) between overall adaptive capacity and one vulnerability dimension. OLS trend lines represent regression fits included for visual interpretation only. Panels (a)–(c) show the three component vulnerability dimensions, while panel (d) shows overall vulnerability. ***p < .001.

All scatterplots showed downward trends. Overall vulnerability had the strongest negative association with adaptive capacity (ρ = −0.928), followed by environmental vulnerability (ρ = −0.857) and sociocultural vulnerability (ρ = −0.785). The association with economic vulnerability was weaker but remained substantial (ρ = −0.546). This pattern indicates that higher institutional adaptive capacity is associated with lower educational vulnerability, but may not fully address economic vulnerability.

Considering the nested structure of respondents within the 24 educational institutions, the ICC analysis (Supplementary Tables S5–S6) indicated substantial institutional clustering for adaptive capacity (ICC(1) = 0.546; ICC(2) = 0.936) and overall vulnerability (ICC(1) = 0.566;

ICC(2) = 0.941). The cluster-bootstrap sensitivity analysis further indicated that the observed associations remained robust after accounting for institutional clustering (Table 5).

Table 5: Spearman correlations between adaptive capacity and vulnerability with cluster-bootstrap confidence intervals

Vulnerability dimension	Spearman's ρ	Cluster-bootstrap 95% CI
Environmental	−0.857	−0.905 to −0.762
Socio-cultural	−0.785	−0.880 to −0.619
Economic	−0.546	−0.708 to −0.356
Overall vulnerability	−0.928	−0.955 to −0.854

The study then classified institutions into three adaptive capacity tertiles (low, medium, and high) and compared vulnerability scores across the groups using the Kruskal–Wallis test (Figure 5). Significant differences were observed across all vulnerability dimensions ($p < .001$). Vulnerability scores decreased progressively from the low- to the high-adaptive-capacity group.

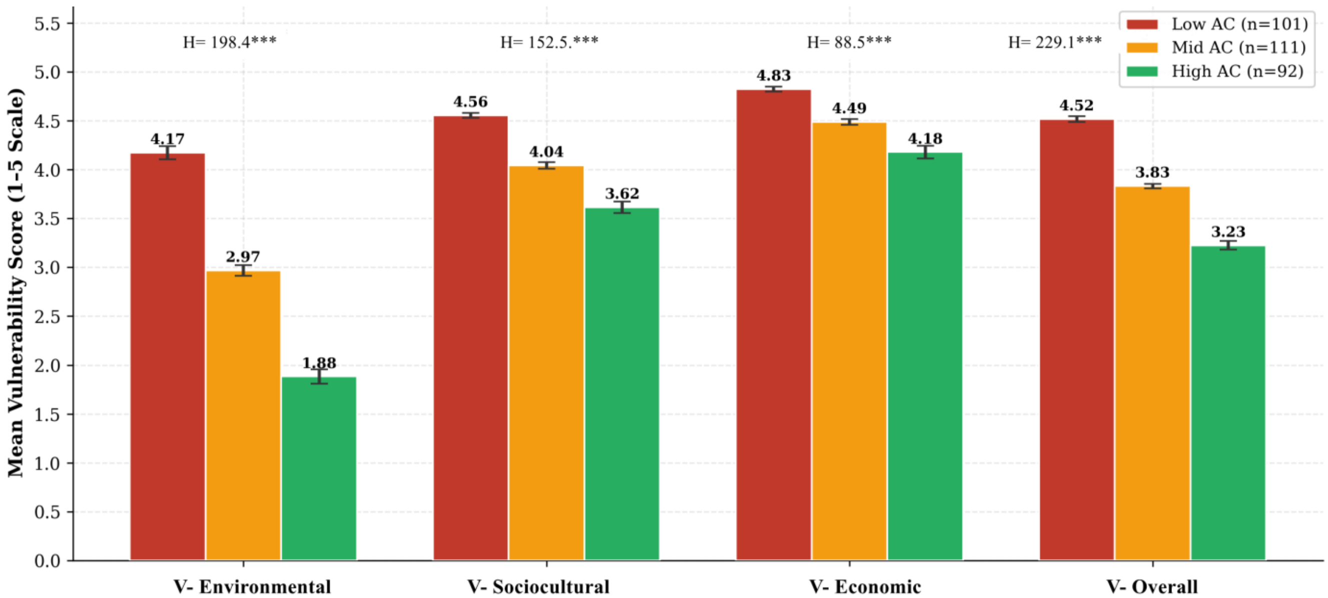

Figure 5: Mean Vulnerability Scores by Adaptive Capacity Tertile Group (n = 304). Error bars represent ±1 SE. H = Kruskal–Wallis statistic. *p < .001 for all comparisons.

Environmental vulnerability showed the largest decline, decreasing from 4.17 in the low adaptive capacity group to 1.88 in the high adaptive capacity group (H = 198.4). Sociocultural vulnerability also declined, from 4.56 to 3.62 (H = 152.5), while economic vulnerability showed a smaller decline, from 4.83 to 4.18 (H = 88.5). Overall vulnerability decreased from 4.52 to 3.23 across the same groups (H = 229.1).

Post hoc pairwise comparisons were conducted using Mann–Whitney U tests with Bonferroni correction. All three adaptive capacity groups differed significantly from one another across all four vulnerability dimensions (all adjusted $p < .001$). Effect sizes were large for overall vulnerability ($\varepsilon^2 = 0.756$), environmental vulnerability ($\varepsilon^2 = 0.655$), and sociocultural vulnerability ($\varepsilon^2 = 0.503$), while the effect size for economic vulnerability was moderate ($\varepsilon^2 = 0.292$). The difference between the low- and high-adaptive-capacity groups was substantial across all dimensions, with rank-biserial correlations of −0.99 for overall vulnerability, −0.95 for environmental vulnerability, −0.90 for sociocultural vulnerability, and −0.64 for economic vulnerability.

The differences between the medium- and high-adaptive-capacity groups were comparatively smaller. The effect remained large for overall vulnerability ($r = -0.82$) and environmental vulnerability ($r = -0.75$), moderate for sociocultural vulnerability ($r = -0.46$), and small for economic vulnerability ($r = -0.29$). The magnitude of the differences was therefore greatest for environmental vulnerability and smallest for economic vulnerability. Supplementary calculations for the associations between adaptive capacity and the vulnerability dimensions are provided in Supplementary Tables S7–S9. Overall, these findings demonstrate a clear inverse association between adaptive capacity and vulnerability.

5 Discussion

This study demonstrates that the strength of the association between adaptive capacity and educational vulnerability varies across different vulnerability dimensions. The potential effectiveness of education-based adaptation depends partly on the types of vulnerability within an institution’s sphere of influence. Adaptive capacity was strongly associated with environmental vulnerability, moderately associated with sociocultural vulnerability, and more weakly associated with economic vulnerability. This pattern suggests that educational institutions may have greater capacity to address direct physical risks, more limited influence over household and community-level pressures, and comparatively little influence over structural economic conditions beyond their control.

The strongest association was observed between adaptive capacity and environmental vulnerability. This finding is plausible because many indicators contributing to adaptive capacity, such as structural maintenance, emergency supplies, sanitation, and disaster planning, directly address the physical conditions that contribute to environmental vulnerability. Investment in these measures can reduce damage to classrooms and learning materials, improve access following floods, and support the faster restoration of educational activities (Feinstein & Mach, 2020; Singh & Shah, 2022). Similar evidence has been reported in Bangladesh and other flood-prone settings. Following Cyclone Aila,

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Parvin et al. (2022) identified prolonged school closures associated with damage to buildings and educational materials, while Lassa et al. (2023) found that the condition of school facilities was an important factor influencing the speed of educational recovery following disasters in Indonesia. Studies from Bangladesh likewise indicate that limited preparedness can increase environmental vulnerability and prolong disruptions to education (Ali et al., 2018; Hoq et al., 2021; Pal et al., 2023). The widespread damage caused by the 2022 flash floods (NAWG, 2022) further illustrates the importance of physical preparedness for educational continuity in the Haor region.

The association with sociocultural vulnerability presents a different pattern. Schools cannot directly determine household decisions, but they may influence how families and communities respond during crises. Child labour, early marriage, seasonal migration, and prolonged absenteeism are primarily household coping responses that can emerge following economic shocks rather than directly from school conditions (Alston et al., 2014; Sarker et al., 2019). In flood-prone areas of Bangladesh, girls may be withdrawn from school for early marriage, while boys may temporarily leave education to engage in fishing or seasonal labour following declines in household income (Farid et al., 2021). Previous studies have shown that such coping strategies can increase absenteeism and school dropout during and after floods (Abedin & Khatun, 2019; Dey et al., 2021). Although schools cannot eliminate these pressures, the present findings suggest that stronger institutional adaptive capacity is associated with lower sociocultural vulnerability. Parent–teacher communication, emergency notification systems, and community outreach were among the stronger adaptive-capacity indicators in this study. Mutch (2023) argues that such mechanisms can strengthen social capital and enable schools to function as trusted community institutions during crises. Saikia and Mahanta (2024) reported a similar pattern in the flood-prone char areas of Assam, where institutional presence was found to be more influential than institutional resources. These findings suggest that adaptive capacity may support educational continuity through both infrastructure and sustained relationships among schools, students, and communities. However, because attendance, retention, and school reopening were not directly measured, these mechanisms remain plausible explanations rather than empirically confirmed pathways.

The weakest association was observed between adaptive capacity and economic vulnerability, highlighting the limitations of school-based adaptation. Household livelihoods in the Haor region remain heavily dependent on a single Boro rice harvest, which is repeatedly threatened by pre-monsoon flash floods (Ahmed, 2024; Bokhtiar et al., 2024; Parvez et al., 2022). Consequently, income losses often originate outside the education system and cannot be substantially reduced through school-level interventions alone (Björkman-Nyqvist, 2013; Kazianga, 2012; Mottaleb et al., 2015). This may explain why economic vulnerability remained comparatively high even among institutions with higher adaptive capacity. Nevertheless, schools are not entirely without influence. Institutions with greater adaptive capacity may be better positioned to mobilise preparedness funds, coordinate repairs, and secure external support, highlighting the importance of adaptive governance (Hurlbert & Gupta, 2017). Financial preparedness indicators were among the weakest indicators in the present study, suggesting that schools may have limited financial resources to respond to major disasters.

These findings are consistent with the constraints-and-limits framework proposed by Dow et al. (2013). Their distinction between soft limits, where barriers may be overcome through additional resources and governance, and hard limits, where effective response options are unavailable, provides a useful interpretation of the present findings. Thomas et al. (2021) synthesised evidence from more than 1,600 adaptation studies and similarly concluded that economic constraints are concentrated at the household level, while institutional adaptation is constrained primarily by finance and governance. The findings of the present study broadly align with this pattern. Reducing household economic vulnerability requires broader fiscal transfers and social protection, representing a soft limit from the perspective of the wider education system. For individual schools, however, limited authority over household income represents a harder constraint. Previous studies suggest that educational institutions may become more resilient when integrated into wider disaster financing and governance systems rather than relying solely on their own limited budgets (Katongole, 2020; Shah et al., 2020a; Shah et al., 2020b; Srikandini et al., 2022).

Overall, the findings suggest that educational resilience develops from the institution outward. Schools appear better positioned to address risks associated with infrastructure and institutional management, while their influence over participation through community relationships is more limited and their capacity to address structural economic conditions affecting household educational decisions is weaker. This perspective views resilience as the result of addressing multiple, interconnected vulnerabilities rather than relying on isolated adaptation measures (Didham & Ofei-Manu, 2020; Papathoma-Köhle et al., 2021; Walker et al., 2022). It is consistent with the Comprehensive School Safety Framework (Global Alliance for Disaster Risk Reduction & Resilience in the Education Sector [GADRRRES], 2022), which emphasises safe facilities, effective disaster management, supportive policies, and institutional coordination. Similarly, UNICEF (2025) argues that maintaining learning during recurrent climate-related disasters requires coordinated investments beyond the school level.

These findings have several practical implications. Strengthening school resilience requires financial resources in addition to planning. Allocating dedicated disaster-preparedness funds within Upazila budgets could help schools maintain safety measures without diverting resources from routine educational activities. Linking the Primary Education Stipend Program with flood early-warning information from the Flood Forecasting and Warning Centre (FFWC) could potentially provide temporary assistance before household income losses lead to school withdrawal. This approach is consistent with Yunus and Shahana (2018), who found that stipends primarily increased household expenditure on schooling. Prioritising the rapid restoration of school-cum-shelters following emergencies and adjusting examination schedules to minimise overlap with the March–May flood season could also reduce learning disruptions in Haor areas. At the institutional level, schools could prioritise measures that directly strengthen adaptive capacity, including regular pre-monsoon building inspections, disaster management committees linked with union-level committees, annual evacuation drills, updated household contact lists, and regular communication with families. Expanding teacher training to include flood response and psychosocial first aid could further strengthen support for students during and after disasters.

Several limitations should be considered when interpreting these findings. The cross-sectional design relied on respondents' perceptions rather than independently verified institutional records and therefore identifies associations rather than causal relationships. Several educational outcomes were not directly measured. Because comprehensive enrolment and staff registers were unavailable, the sample was non-probability based and cannot be considered fully representative of Tahirpur Upazila. The number of participants varied across locations, and the relatively small number of respondents from Tahirpur Sadar limits the interpretation of comparisons involving this union. Adaptive capacity and vulnerability were assessed using responses from the same participants, which may introduce common-method bias. Although the instrument was reviewed by experts, no formal pilot testing or psychometric validity assessment was conducted. Finally, the study focused on a single Haor upazila and a single flood season, limiting the generalisability of the findings to other regions and temporal contexts. Future research should examine multiple Haor and flood-prone regions over several flood seasons and link institutional adaptive-capacity measures with administrative and longitudinal data to better understand how institutional capacity influences educational adaptation and resilience.

6 Conclusions

This study assessed climate-induced educational disruption in the Haor region of Bangladesh, where recurrent flood events intersect with the physical, academic, and financial resources of educational institutions and the livelihood options of households. In Sunamganj, schools serve not only as learning centres but also as social anchors, emergency shelters, and local recovery points. Therefore, educational disruption should be treated as a central climate-risk issue rather than as a secondary consequence of disasters. The study aimed to assess educational vulnerability across three dimensions (environmental, sociocultural, and economic) and examine the association between institutional adaptive capacity and vulnerability. A total of 304 respondents affiliated with 24 educational institutions were surveyed in Tahirpur, Sunamganj.

The results showed a strong association between higher adaptive capacity and lower vulnerability. Overall adaptive capacity had a strong negative relationship with overall vulnerability ($\rho = -0.928$). The strongest association was observed for environmental vulnerability ($\rho = -0.857$), followed by sociocultural vulnerability ($\rho = -0.785$). Economic vulnerability also showed a negative association with adaptive capacity, although the relationship was weaker ($\rho = -0.546$). Corrected item–total correlations further indicated that routine inspections, environmental preparedness, disaster training, planning and curriculum integration, and coordination were strongly aligned with institutional adaptive capacity, whereas several financial indicators showed comparatively weaker associations.

These findings suggest that climate-resilient education policies should strengthen practical institutional preparedness while recognising the limits of school-level adaptation in addressing household economic vulnerability. Priorities should include pre-monsoon infrastructure maintenance, disaster preparedness and training, early-warning and information systems, disaster risk reduction-integrated planning, and stronger institutional coordination. These measures should be complemented by broader livelihood and social-protection support to sustain educational continuity following floods.

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Data Availability: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest: The authors state that they have no financial or personal conflicts of interest that could have influenced the work reported in this paper.

Ethics Statement: This study involved the analysis of data previously collected as part of an independently conducted project through the International Centre for Climate Change and Development (ICCCAD) at Independent University, Bangladesh (IUB). No additional data were collected from human participants for the present study. The analysis was conducted using anonymised, non-identifiable data. The dataset was repurposed for the present research; therefore, no separate ethical approval was obtained for this specific analysis.

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