Measuring Flood Damage to Pond Aquaculture: Satellite Evidence from Bangladesh

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Abstract

Pond aquaculture feeds and employs millions across low- and middle-income countries, but open ponds are vulnerable to increasing flood shocks. We match three rounds of a Bangladeshi household panel to satellite-observed inundation, measuring each household's exposure over the twelve months before its own interview. On the extensive margin, any inundation lowers the probability of operating a pond by 2.9 percentage points, a 16% relative decline. On the intensive margin, severe floods, which inundate more than half the surrounding area, reduce yield by 48%, revenue by 47% and profit by about 18,500 taka. We find no evidence that any coping margin compensates, and household income falls by more than the pond loss alone. Such floods cost the sector about 26 million USD a year, a cost projected to rise to 30–39 million by late century.

Keywords: floods; aquaculture; damage measurement; Bangladesh; satellite data

JEL: Q22; Q54; O13; Q12

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1 Introduction

Fisheries and aquaculture supply at least a fifth of the animal protein of 3.2 billion people and employ 62 million, 85% of them in Asia (FAO, 2024). In Bangladesh, pond aquaculture's expansion held fish prices down and raised consumption among the poorest households (Toufique and Belton, 2014). On the saline coast the sector is itself an adaptation strategy: as dry-season salinity rises, land moves from crops into shrimp and crab farming (Haque, 2025).

Yet ponds are exposed to flooding: a pond is a standing body of water behind a raised margin, and when flood water tops it the stock swims out, immediately and irreversibly. Bangladesh lies at the outlet of the Ganges–Brahmaputra–Meghna basin, where flood peaks are projected to rise (Gädeke et al., 2022). Deepening ponds for irrigation storage is profitable (Kabir et al., 2025); the cost and benefit of raising their margins above the flood line are unquantified.

Climate damage to agriculture is well documented (Dell et al., 2014), and satellite flood data have been used to study self-reported exposure, urban activity, employment, migration and schooling (Guiteras et al., 2015; Kocornik-Mina et al., 2020; Patel, 2024). To our knowledge, none of this work examines pond aquaculture, or whether farmers can absorb its flood losses.

We fill that gap by matching a Bangladeshi household panel to satellite flood maps. Inundation of any size lowers the probability of operating a pond by 16% (2.9 percentage points). Among pond operators, floods covering more than half the surrounding land reduce yield by 48%, revenue by 47% and profit by about 18,500 taka. We find no evidence that coping compensates, and household income falls by more than the pond loss. These floods cost the sector about 26 million USD a year, rising to 30–39 million by late century.

2 Data and Methodology

Data. We use three rounds of the Bangladesh Integrated Household Survey (BIHS), a nationally representative rural panel fielded in 2011–12, 2015 and 2018–19. Its aquaculture module records pond area, species, input costs, harvest and sales value. We drop open-water fishing, which reports no pond area. We construct yield (kg per hectare), revenue (harvest at the household's own median sales price), input cost, profit, participation and pond area (in decimals; one decimal is 40.5 m^2), deflating taka to 2018–19 prices (World Bank CPI). Revenue and cost are winsorized at round-specific 99th percentiles and profit is their difference, so their level coefficients add up exactly.

Flood exposure. Inundation comes from the Global Flood Database v1.4 (Tellman et al., 2021), which maps the maximum extent of Dartmouth Flood Observatory events at 250 m resolution, for the 56 events mapped over Bangladesh in 2000–2018. Household exposure is the inundated share, excluding permanent water, of a fixed square window, 3.25 km on a side, centered on the union's interior point, maximized over events in the household's 12-month pre-interview window. We prefer the fixed window because it holds the denominator constant, so a given share is the same quantity of water everywhere; the Supplementary Material (SI) reports exposure built on administrative union boundaries.

Specification. For outcome Y of household i in round t,

$$Y_{it} = \sum_b \beta_b \mathbf{1}\{S_{it} \in b\} + \gamma' X_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{1}$$

where S_{it} is the inundated share. We report two specifications: an indicator for any inundation, and that indicator split at half the window into $\leq$50% and >50%; we call the upper bin a severe flood. In both, household-rounds with no inundation are the omitted category (2,196 in the harvest sample, 1,577 of them outside every mapped flood footprint). α_i and δ_t are household and round fixed effects. Household effects absorb pond quality,

operator skill and baseline flood risk; round effects absorb national shocks. X_{it} holds heat-wave days and maximum five-day monsoon rainfall in the same window, from ERA5 and CHIRPS by inverse-distance weighting, with household size, head age, and baseline land, education and female headship interacted with round. Yield and revenue enter as inverse hyperbolic sines, log-like away from the origin but defined at a total-loss year's zeros; pond area, zero without a pond, stays in decimals, and profit, which can be negative, in taka. The transform is not unit-free (Chen and Roth, 2024), so the SI reports levels too. Standard errors are clustered by union. Identification comes from within-farm changes in inundation across rounds, with 115 households in 19 unions changing above-half status, and assumes that, conditional on α_i and δ_t, the timing of these changes is as good as random.

3 Results

Exit. Any inundation lowers the probability of operating a pond by 2.9 percentage points ($p < 0.01$, 18,436 household-rounds), a 16% decline against a base of 18%. Split at half the window, the decline is significant at or below 50%, but the two bins are not distinguishable ($p = 0.81$). Pond area rises 3.9 decimals after severe floods (Table 1, $p = 0.01$) but turns to -0.5 ($p = 0.51$) when capped at the 95th percentile (SI Section S1). Severe floods also raise survey attrition by 5.9 percentage points ($p < 0.01$), though not detectably among pond operators (SI Table S12).

Damage. Table 1 reports equation (1). In Panel A, any inundation has no detectable effect on yield (-0.238, $p = 0.17$). For severe floods, on 117 household-rounds, the asinh yield coefficient is -0.657 ($p = 0.03$), a loss of 48%; revenue -0.630 ($p = 0.02$); profit $-18{,}504$ taka ($p = 0.04$), between $-5{,}357$ and $-36{,}103$ across winsorization cuts (SI Table S15). At or below half, the estimates are small and insignificant; for yield the two bins differ only marginally ($p = 0.09$). Because these estimates condition on operating, the loss is understated if the worst-hit stop.

Robustness. The severe-flood yield loss keeps its sign in every check, though not always its significance. It is -0.539 in logs on positive yields ($p = 0.03$) and negative but imprecise in kg/ha (SI Table S11). Moving the split from 40% to 60% of the window leaves it negative throughout and significant at the 50 and 55% cutoffs (SI Table S4). Measured over the union polygon it is -0.625 ($p = 0.04$), although on that measure the lower bin is also significantly negative (SI Table S2). Conley spatial standard errors (Conley, 1999) are larger than the clustered ones and put the p-values for yield, revenue and profit between 0.07 and 0.09 (SI Table S10); counting nested fixed effects in the small-sample correction gives $p = 0.10$ for yield. Without round 3, which the satellite record barely covers, the yield and revenue coefficients shrink to -0.341 and -0.383 and lose significance; equality across rounds is not rejected for yield or revenue ($p = 0.25$, 0.78) but is for profit ($p = 0.03$; SI Table S9).

No evidence of offsetting. We find no detectable response to severe floods on any coping margin (SI Table S17). In Table 2, total income falls 36,805 taka ($p = 0.01$), about twice the aquaculture profit loss; its components sum to 35,308, the gap reflecting winsorization of the total. Crop sales are the second-largest component, down 8,837 taka ($p = 0.04$). Labor income counts wages and salaries only (SI Table S18).

4 Back-of-the-Envelope Costs

The calculation multiplies the annual probability of a severe flood, 0.057; a per-event harvest loss of about 13,600 taka implied by the yield effect; and 2.82 million inland fish farmers (Department of Fisheries, 2024), giving around 26 million USD a year (SI Table S19). Gädeke et al. (2022) project Ganges–Brahmaputra–Meghna peak flows 16–60% higher by late century (2070–2099); scaling observed inundation accordingly raises the cost to 30–39 million. We treat the loss as an annual flow, although revenue and profit losses persist beyond the flood year (SI Table S8). It omits exit and moderate floods but overstates producing households, so the net bias is unclear.

5 Conclusion

Floods lower pond operation and cut the harvest of those who continue, and we find no evidence that either loss is made up elsewhere. The mean pond-profit loss from a severe flood, about 18,500 taka, is 15% of mean annual income among aquaculture households (125,754 taka). Damage on that scale belongs in appraisals of embankment and drainage investment, alongside crop and housing losses.

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Declaration of generative AI use

The authors used Anthropic's Claude (Claude Opus 5.5, through Claude Code) for coding and debugging the analysis pipeline, for literature search, for drafting assistance, and for editing: grammar, sentence structure, and shortening some paragraphs. All data construction, specifications, results and conclusions are the authors' own, and the authors take full responsibility for the content of this article.

Data availability statement

ERA5, CHIRPS and the Global Flood Database v1.4 (Tellman et al., 2021) are openly available. BIHS microdata are available from the International Food Policy Research Institute via Harvard Dataverse. Code will be archived in a public repository on acceptance.

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Table 1: Flood inundation and aquaculture outcomes, against household-rounds with no inundation

	Yield	Revenue	Profit	Participation	Pond area
A. Any inundation					
Any inundation	−0.238	−0.179	−2,974	−0.029***	0.671*
	(0.173)	(0.172)	(4,423)	(0.010)	(0.399)
Heat-wave days (per 10 days)	0.021	0.030	646	−0.005	−0.337***
	(0.045)	(0.051)	(1,445)	(0.004)	(0.135)
Rx5day (per 100 mm)	0.174	0.161	972	0.018*	0.333
	(0.128)	(0.140)	(3,214)	(0.009)	(0.227)
Observations	2,580	2,580	2,580	18,436	18,436
B. Split at half the window					
Inundated ≤50%	−0.076	−0.005	3,034	−0.029***	−0.009
	(0.185)	(0.190)	(3,499)	(0.010)	(0.288)
Inundated >50%	−0.657**	−0.630**	−18,504**	−0.025	3.932***
	(0.304)	(0.268)	(8,804)	(0.018)	(1.508)
Heat-wave days (per 10 days)	0.016	0.026	488	−0.005	−0.259**
	(0.045)	(0.051)	(1,463)	(0.004)	(0.129)
Rx5day (per 100 mm)	0.221*	0.211	2,708	0.017*	0.011
	(0.132)	(0.143)	(3,348)	(0.010)	(0.239)
Observations	2,580	2,580	2,580	18,436	18,436
Household FE	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Model	asinh	asinh	OLS	LPM	OLS

Notes: Inundated share of a 3.25 km square window centered on the union's interior point, the maximum across events in the household's 12-month pre-interview window. In both panels the omitted category is household-rounds with no inundation at all, 2,196 of the yield sample; Panel A contrasts any inundation against them, Panel B splits that contrast at half the window (267 household-rounds at or below half, 117 above). Participation and pond area are estimated on every household in the sample, pond area in decimals with a zero for households operating no pond; the harvest outcomes on households operating a pond. Heat-wave days and Rx5day enter as controls, with household size, head age, and baseline education, female headship and land × round. Household and round fixed effects; standard errors clustered by union. Stars follow the p-value as displayed, rounded to two decimals: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

Table 2: Severe flooding and household income: components and totals

Outcome	Estimate	Std. error	p	N
A. Income components (taka, levels)				
Aquaculture profit	−18,504**	8,804	0.04	2,580
Crop sales value	−8,837**	4,342	0.04	2,580
Livestock sales value	−295	7,394	0.97	2,580
Non-farm enterprise profit	−4,533	9,068	0.62	2,580
Labor income	−3,139	5,506	0.57	2,580
B. Income aggregates (taka, levels)				
Total income	−36,805***	13,648	0.01	2,580
excluding labor income	−33,801***	13,605	0.01	2,580
adding back module-C self-employment	−55,824**	22,923	0.02	2,580

Notes: Each row regresses the named outcome on both inundation bins and reports the severe-flood (>50%) coefficient, with heat-wave days, Rx5day, household size, head age, and baseline education, female headship and land × round as controls, and household and round fixed effects. Both panels are OLS on taka levels. The components in Panel A sum to −35,308 taka against −36,805 for total income in Panel B; the gap arises from winsorizing the total as a whole. Labor income is wage and salary earnings only; the last row adds back self-employment, which the profit rows largely count already. Sample: aquaculture households; standard errors clustered by union. Stars follow the p-value as displayed, rounded to two decimals: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.