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Saturation before accumulation: recurrent climate-induced displacement and the sequenced erosion of livelihood capitals in coastal Ghana

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Saturation before accumulation: recurrent climate-induced displacement and the sequenced erosion of livelihood capitals in coastal Ghana

Abstract

Climate-induced displacement on low-lying African coasts is rarely a single event; households are displaced, return, and are displaced again. Whether each additional episode deepens livelihood loss, or whether most damage occurs early, remains unquantified. This study examines how the frequency of climate-induced displacement relates to multidimensional livelihood erosion in four tidal-flood and erosion hotspots of Keta Municipality, Ghana. A survey of 364 households was combined with focus groups (n = 24) and three key-informant interviews. Eight deprivation indicators were mapped onto financial, physical, human and social livelihood capitals and aggregated into a weighted deprivation score and an Alkire–Foster multidimensional headcount. Fractional logit, logistic and Poisson models estimated adjusted dose–response associations across four exposure levels: never, once, two to three and more than three displacements in five years. Livelihood deprivation rose from an adjusted 0.40 among never-displaced households to 0.52 after one displacement and 0.63 after two to three, then levelled off (0.61) beyond three episodes. The adjusted probability of multidimensional deprivation was 0.81 after two to three displacements, against 0.44 for never-displaced households. Capitals eroded in sequence: most financial and physical deprivation occurred with the first displacement, whereas access to education and healthcare accumulated only with repeated displacement. Formal employment protected income and assets but not access to services, so displaced formal and place-dependent households converged. Results were robust to alternative weights, estimators and cut-offs. Support therefore needs to be front-loaded, through rapid asset and income replacement after the first displacement, and complemented by protected access to schooling and health services for households facing recurrent displacement.

Keywords: climate-induced displacement; livelihood capitals; multidimensional deprivation; dose–response; coastal flooding; Ghana.

1. Introduction

Weather-related hazards are now the largest driver of new internal displacement worldwide. The Internal Displacement Monitoring Centre recorded 45.8 million disaster-related internal displacements in 2024, one of the highest annual totals on record (IDMC, 2025). Much of this movement is short-distance and temporary: households leave flooded homes, shelter with kin or in public buildings, and return when the water recedes (Black et al., 2013). On low-lying coasts exposed to tidal flooding and shoreline retreat, the cycle repeats. For these populations, displacement is not a one-off shock but a recurrent condition that unfolds over years (Ayeb-Karlsson et al., 2016; Adams, 2016).

Researchers have documented the livelihood consequences of displacement extensively. Displaced households lose income, productive assets, and access to services, and face higher costs for food, water, and shelter (Hallegatte et al., 2017; Warner & van der Geest, 2013). The Sustainable

Livelihoods Framework (SLF) organises these losses around the depletion of financial, physical, natural, human and social capitals (Scoones, 1998; DFID, 1999; Bebbington, 1999). Loss-and-damage research adds that many of these harms are non-economic and difficult to reverse (Tschakert et al., 2019; Mechler et al., 2019).

Yet most quantitative studies treat displacement as a binary exposure: a household either has or has not been displaced. This framing cannot distinguish between two plausible but very different dynamics. Under a cumulative ratchet, each additional episode erodes a further slice of the asset base, so deprivation rises steadily with frequency (Carter & Barrett, 2006; Carter et al., 2007). Under early saturation, the first displacement destroys most of what can be lost, and later episodes add comparatively little. The two dynamics carry different policy implications. A ratchet calls for support that scales with the number of episodes; saturation calls for support that is concentrated at the first displacement. A binary exposure measure averages over both and therefore cannot inform the timing of assistance.

A second limitation is the tendency to analyse livelihood outcomes one at a time, typically income loss, asset loss or cost escalation in separate models. Livelihood capitals are interdependent, however. Losing a canoe affects income, the cost of reaching a new fishing site, and, eventually, a household's ability to pay school fees (Bebbington, 1999; Renn et al., 2022). Counting-based multidimensional measures, developed for poverty analysis (Alkire & Foster, 2011; Alkire & Santos, 2014), offer a way to assess whether deprivations cluster within the same households and which capitals drive the overall burden. They have rarely been applied to displacement.

Ghana's eastern coast illustrates both problems. The Keta area of the Volta Delta is among West Africa's most dynamic shorelines, shaped by subsidence, sediment deficit, and a high-energy wave climate (Addo et al., 2018; Jayson-Quashigah et al., 2013). Tidal flooding and erosion repeatedly displace households in Keta, Anyako, Seva and Havedzi. Drone monitoring and flood-scenario modelling document recurrent inundation and growing risk to housing, roads and public services (Appeaning Addo et al., 2018; Tumawu et al., 2024). Existing work in the municipality is largely qualitative or concerned with hazard mapping. The relationship between how often households are displaced and how deeply their livelihoods are eroded has not been measured.

This study addresses that gap. It asks three questions. (i) Does livelihood deprivation increase with the frequency of climate-induced displacement, and if so, does it follow a cumulative or a saturating pattern? (ii) Do financial, physical, human and social capitals erode at the same pace as displacement recurs? (iii) Does formal employment, which is detached from coastal resources, buffer households against displacement-related deprivation? The study makes three contributions. Empirically, it provides, to our knowledge, the first household-level dose–response estimates for recurrent displacement on Ghana's coast. Methodologically, it adapts the Alkire–Foster counting approach to displacement-related livelihood deprivation and pairs it with fractional-response models suited to bounded scores. Conceptually, it shows that capitals erode sequentially rather than simultaneously, with direct consequences for when and how support is delivered.

2. Conceptual framework

The analysis combines the asset logic of the SLF with the dynamic reasoning of the poverty-trap and systemic-risk literatures (Fig. 2). In the SLF, households draw on a portfolio of capitals to pursue livelihood strategies, and shocks act through the vulnerability context by depleting that portfolio (Scoones, 1998, 2009; DFID, 1999). Displacement is a particularly severe shock because it separates households from place-bound assets (boats, nets, farmland, market stalls, customers) while raising their living costs (Hallegatte et al., 2017).

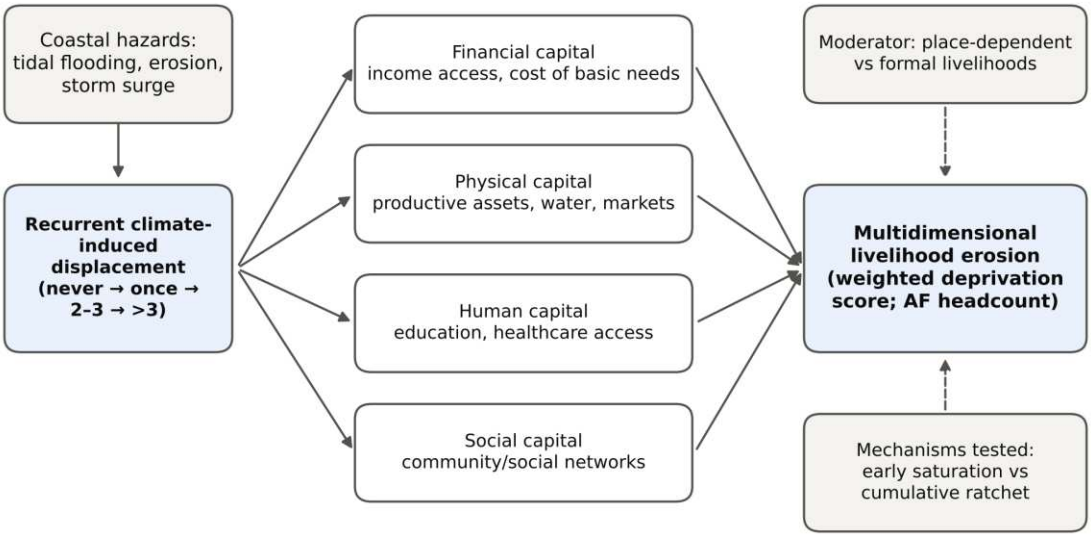


Fig. 2. Conceptual framework. Recurrent displacement acts on four livelihood capitals, which combine into multidimensional livelihood erosion; the shape of the gradient (cumulative ratchet vs early saturation) and buffering by livelihood type are tested empirically.

Asset-based models of poverty traps add a temporal dimension. When repeated shocks push a household's assets below the threshold needed to sustain its livelihood, recovery stalls and further shocks deepen deprivation (Carter & Barrett, 2006; Carter et al., 2007). Systemic-risk perspectives similarly emphasise that losses can cascade across interconnected systems and compound over time (Renn et al., 2022). Both lines of reasoning predict a cumulative ratchet: deprivation should rise with each additional displacement.

There is also a plausible counter-argument. Many coastal households hold small asset stocks, and much of what can be destroyed may be lost in the first major event. After that, a ceiling is reached: income cannot fall much further, and there is little left to lose. Households that remain through repeated displacement may also have the strongest place attachment or the fewest exit options (Adams, 2016; Black et al., 2013; Mortreux & Barnett, 2009), and some develop routinised coping practices. These mechanisms predict early saturation: a steep rise in deprivation with initial displacement, followed by a plateau.

The two mechanisms need not apply equally to all capitals. Financial and physical capitals are directly exposed: income stops when fishing stops, and the water itself destroys assets. Human-capital outcomes, such as children's schooling and access to health care, may instead deteriorate gradually as households run down savings, relocate further from services, or defer payments across successive episodes (Hoddinott, 2006; Dercon, 2004). The shape of the dose–response relationship may therefore differ by capital, a possibility we examine without a prior directional hypothesis.

Finally, livelihood type may condition exposure. Fishing, fish processing, trading and artisanal work depend on coastal space and local markets, whereas salaried formal employment provides income that is largely independent of local hazard conditions (Cutter et al., 2003; Adger, 2006). If formal employment protects households, displacement-related deprivation should be lower among formally employed households.

These arguments yield two competing hypotheses, one exploratory question and one further hypothesis:

- **H1a (cumulative ratchet).** Livelihood deprivation increases monotonically with each additional displacement episode.
- **H1b (early saturation).** Livelihood deprivation increases sharply with initial displacement and then levels off at higher frequencies.
- **RQ2 (sequencing, exploratory).** Do financial, physical, human and social capitals follow the same dose–response shape?
- **H2 (buffering).** The association between displacement and deprivation is weaker for formally employed households than for households with place-dependent livelihoods.

3. Materials and methods

3.1 Study area

Keta Municipality lies on Ghana's eastern coast, east of the Volta estuary and about 160 km from Accra (Fig. 1). It covers about 1,086 km², roughly a third of which is water, dominated by the Keta Lagoon (Ghana Statistical Service, 2021). The coastal strip is a narrow, low-lying sand barrier between the lagoon and the Gulf of Guinea. Subsidence, sediment starvation linked to upstream damming and a high-energy wave climate drive some of the fastest shoreline retreat in the country (Addo et al., 2018; Jayson-Quashigah et al., 2013; Boateng, 2012). Since the early 2000s, sea defence works have protected parts of Keta town, but tidal flooding continues to inundate settlements along the barrier and lagoon shore (Appeaning Addo et al., 2018; Tumawu et al., 2024).

The study examined four communities: Keta, Anyako, Seva, and Havedzi. They were selected purposively because they experience periodic tidal flooding and repeated household displacement. Their combined population is 15,901 (Ghana Statistical Service, 2021). Local livelihoods are dominated by marine and lagoon fishing, fish processing and trading, supplemented by shallot and vegetable farming, artisanal trades and a smaller formal sector in teaching, health and public administration.

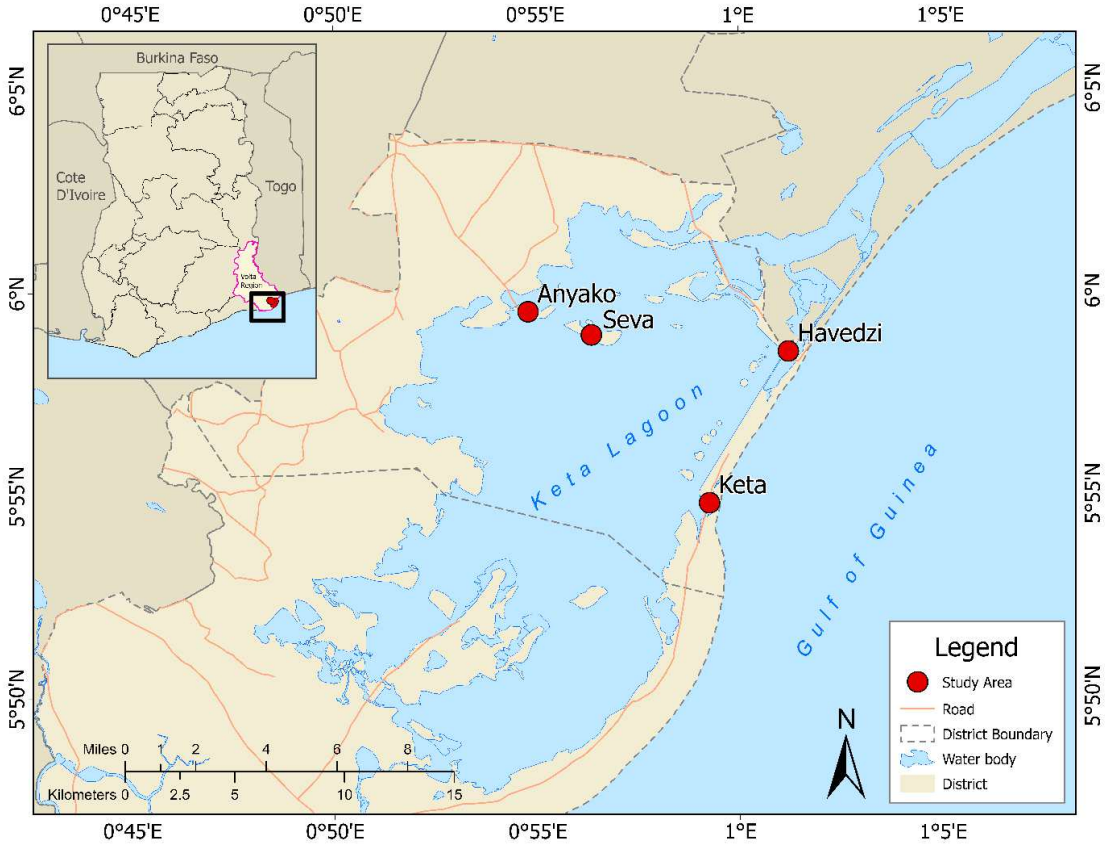


Fig. 1. Location of the four study communities (Anyako, Seva, Havedzi and Keta) on the Keta Lagoon and the Gulf of Guinea, Keta Municipality, Volta Region, Ghana. Source: Geological Survey Department, KNUST.

3.2 Design and sampling

The study used a convergent mixed-methods design, collecting survey and qualitative data in the same period and integrating them during interpretation (Creswell & Plano Clark, 2018). The survey sample size was calculated using Cochran's (1977) formula for a finite population of 15,901 (95% confidence, ±5% margin, p = 0.5), yielding 364 respondents. The sample was allocated in proportion to community population, and households were selected by systematic sampling from a random start along each settlement (sampling interval ≈ 42). One adult (≥ 18 years) per household, the head or a knowledgeable adult member, was interviewed face-to-face using KoBoCollect. The questionnaire was pre-tested with 40 household heads in Kedzi, a nearby erosion-affected community outside the sample.

The qualitative component comprised four focus group discussions (FGDs), one per community, with six purposively selected household heads each (n = 24), and key informant interviews (KIIs) with the Keta Municipal NADMO officer, planning officer and social welfare officer. FGDs and KIIs were transcribed and analysed thematically (Braun & Clarke, 2006). This study uses qualitative material to interpret the mechanisms behind the statistical patterns.

3.3 Measures

Respondents reported whether the household had ever been displaced from its home by flooding, sea erosion or another climate-related event, and, if so, how many times in the past five years. Responses define a four-level ordinal exposure: never displaced (n = 49), once (n = 59), two to three times (n = 220) and more than three times (n = 36).

Eight binary indicators, each referring explicitly to the effects of displacement or climate hazards, were mapped onto four livelihood capitals (full definitions, weights and prevalence are reported in Section 4.2). Financial capital comprises reduced access to stable income and higher costs for basic household needs. Physical capital comprises loss of productive property (land, equipment, or buildings) and difficulty accessing clean water, sanitation, and markets. Human capital comprises difficulty accessing education and healthcare. Social capital comprises difficulty accessing community and social networks. Natural capital was not measured separately; its loss is reflected indirectly in fishing equipment, farmland and market disruption.

Following the nested-weighting convention of the global Multidimensional Poverty Index (Alkire & Santos, 2014), each capital received an equal weight of 1/4, divided equally among its indicators. The household deprivation score is

$$c_i = \sum_{j=1}^{8} w_j \; g_{ij}, \qquad \sum_{j} w_j = 1, \qquad c_i \in [0,1] \qquad (1)$$

where g_{ij} = 1 if household i is deprived in indicator j. Indicator weights are 0.125 (financial indicators), 0.083 (physical), 0.125 (human) and 0.25 (social). Because the score is formative (it counts distinct deprivations rather than measuring a single latent trait), internal consistency is not a validity criterion; the Kuder–Richardson coefficient (KR-20 = 0.50) is reported for information only.

Using the Alkire–Foster (AF) dual cut-off method (Alkire and Foster, 2011), a household is classified as multidimensionally deprived when $c_i \geq k$. The main cut-off is k = 0.50, meaning deprivation in at least half of the weighted indicators. Because 90% of households met the conventional k = 1/3 threshold, a higher cut-off was needed to discriminate between groups. Results are reported for k from 0.25 to 0.75. For each group, the headcount ratio H (share deprived), the intensity A (mean score among the deprived) and the adjusted headcount $M_0 = H \times A$ were computed, and M_0 was decomposed into the percentage contribution of each indicator and capital.

Models adjust for respondent sex, age (per 10 years), education (ordinal, 1 = none to 5 = tertiary), household size, years of residence in the community (per 10 years), presence of a household member with disability, main livelihood and community. Livelihood was grouped into fishing (reference), trading, formal employment and a residual category of farming, artisanal and other informal work. Income and prior displacement-induced relocation were omitted from the main models because both may lie on the causal pathway from displacement to deprivation; they were added in a sensitivity analysis.

3.4 Statistical analysis

Analysis proceeded in four steps.

Step 1: descriptive gradients and co-occurrence. Indicator prevalence was compared across exposure levels using χ^2 tests (ever vs never displaced) and logistic trend tests across the four levels. Clustering of the three core financial and physical losses was assessed by comparing the observed share of households experiencing all three with the share expected under independence.

Step 2: dose–response models (H1a, H1b). Because c_i is a bounded proportion with mass at intermediate values, the primary model is a fractional logit (Papke and Wooldridge, 1996):

$$E(c_i \mid \mathbf{x}_i) = \Lambda\left(\alpha + \sum_{l=1}^{3} \beta_l D_{il} + \mathbf{x}_i'\boldsymbol{\gamma}\right) \qquad (2)$$

where Λ is the logistic function, D_{il} are indicators for once, two to three and more than three displacements (reference = never) and $\mathbf{x}_i$ is the covariate vector. Results are reported as adjusted predicted means and average marginal effects (AMEs) obtained by recycled predictions (Williams, 2012), with 95% confidence intervals from 2,000 parametric simulations of the coefficient vector. H1a implies that AMEs increase at every step; H1b implies a significant first step and a non-significant or negative final step. A Wald test assessed whether the three displaced levels differed. Two complementary models were estimated: a Poisson model of the number of deprivations (0–8), reported as incidence rate ratios (IRRs), and a logistic model of AF multidimensional deprivation at k = 0.50, reported as odds ratios (ORs). All models use heteroskedasticity-robust (HC1) standard errors.

Step 3: capital-specific models (RQ2). The fractional logit was re-estimated separately for the four capital sub-scores (the mean of each capital's indicators). For each, AMEs relative to never-displaced households were computed, and a linear trend across the three displaced levels was tested within the displaced subsample.

Step 4: buffering (H2). A fractional logit with an interaction between ever-displaced status and place-dependent livelihood (all categories except formal employment) estimated whether the displacement effect differs by livelihood. The difference in AMEs between the two livelihood groups was tested by simulation.

Robustness. Seven checks were run: (i) equal weights for all eight indicators; (ii) adding log income and prior displacement-induced relocation; (iii) OLS with HC3 errors; (iv) excluding Seva, the smallest community; (v) an ordered logit of the deprivation count; (vi) the AF cut-off varied from 0.25 to 0.75; and (vii) an E-value for the risk ratio of multidimensional deprivation from a modified Poisson model (Zou, 2004; VanderWeele & Ding, 2017), indicating how strong an unmeasured confounder would need to be to explain away the association. Variance inflation factors were all below 2.4. Analyses were conducted in Python 3.13 with statsmodels 0.15.

4. Results

4.1 Sample profile and exposure

Displacement was near-universal: 315 of 364 households (86.5%) had been displaced at least once, and 256 (70.3%) had been displaced two or more times in the past five years (Table 1). Displaced and never-displaced households were similar in sex, education, household size and income. Displaced respondents were older (43.5 vs 37.0 years, Mann–Whitney $p < 0.001$) and had lived longer in the community (25.6 vs 19.5 years, $p = 0.022$), consistent with longer cumulative exposure. Fishing households made up 41.3% of displaced households, compared with 26.5% of never-displaced households, but the overall association between livelihood and displacement was marginal ($\chi^2(3) = 7.36$, $p = 0.061$). All 18 Seva respondents had been displaced.

Table 1. Sample characteristics by displacement status (N = 364).

Characteristic	All, n (%)	Never displaced, n (%)	Ever displaced, n (%)	p
Total	364 (100)	49 (13.5)	315 (86.5)	
Sex: female	201 (55.2)	30 (61.2)	171 (54.3)	0.451
Age, mean (SD), years	42.6 (13.3)	37.0 (11.8)	43.5 (13.3)	< 0.001
Education				0.488
None	61 (16.8)	5 (10.2)	56 (17.8)	
Primary	31 (8.5)	4 (8.2)	27 (8.6)	
Junior high	119 (32.7)	15 (30.6)	104 (33.0)	
Senior high	85 (23.4)	12 (24.5)	73 (23.2)	
Tertiary	68 (18.7)	13 (26.5)	55 (17.5)	
Main livelihood				0.061
Fishing	143 (39.3)	13 (26.5)	130 (41.3)	
Trading	98 (26.9)	19 (38.8)	79 (25.1)	
Farming, artisanal and other	63 (17.3)	6 (12.2)	57 (18.1)	
Formal employment	60 (16.5)	11 (22.4)	49 (15.6)	

Characteristic	All, n (%)	Never displaced, n (%)	Ever displaced, n (%)	p
Community				0.098
Keta	191 (52.5)	22 (44.9)	169 (53.7)	
Anyako	117 (32.1)	22 (44.9)	95 (30.2)	
Havedzi	38 (10.4)	5 (10.2)	33 (10.5)	
Seva	18 (4.9)	0 (0.0)	18 (5.7)	
Household size, mean (SD)	6.8 (3.9)	6.9 (3.7)	6.8 (4.0)	0.786
Years in community, mean (SD)	24.8 (16.7)	19.5 (14.5)	25.6 (16.8)	0.022
Member with disability	85 (23.4)	6 (12.2)	79 (25.1)	0.073
Monthly income, median (IQR), GHS	800 (500–2,000)	—	—	0.158
Displacements in past 5 years				
Once	59 (16.2)	—	59 (18.7)	
2–3 times	220 (60.4)	—	220 (69.8)	
More than 3 times	36 (9.9)	—	36 (11.4)	

* p-values from χ^2 tests for categorical variables and Mann–Whitney U tests for continuous variables. GHS = Ghana cedi.

4.2 Deprivation profile and its gradient

The eight deprivations were widespread and strongly patterned by exposure (Table 2, Fig. 3). Among all households, 81.9% reported reduced access to stable income, 83.5% higher basic-needs costs and 80.0% loss of productive property. Among displaced households, 87.3%, 88.3%, and 87.3% reported these losses, compared with 46.9%, 53.1%, and 32.7% among never-displaced households. Property loss showed the sharpest contrast ($\chi^2(1) = 78.99$, $p < 0.001$). Market and water access also differed significantly. Healthcare access did not differ between ever- and never-displaced households ($p = 0.112$), but rose significantly across the exposure gradient (trend p <

0.001), from 28.8% among once-displaced households to 66.7% among those displaced more than three times. Loss of social networks was the least common deprivation (19.5%) and was unrelated to exposure.

Table 2. Livelihood deprivation indicators, weights and prevalence (N = 364).

Capital (weight)	Indicator: household reports that displacement or hazards…	Weight	All (%)	Never displaced (%)	Ever displaced (%)	χ^2 (1 df)	Trend p
Financial (1/4)	reduced access to stable income	0.125	81.9	46.9	87.3	46.54***	< 0.001
	increased the cost of basic household needs	0.125	83.5	53.1	88.3	38.15***	< 0.001
Physical (1/4)	caused loss of productive property (land, equipment, buildings)	0.083	80.0	32.7	87.3	78.99***	< 0.001
	made clean water and sanitation harder to access	0.083	80.2	65.3	82.5	7.94**	0.007
	made markets harder to access	0.083	61.5	38.8	65.1	12.40***	< 0.001
Human (1/4)	made education harder to access	0.125	60.2	44.9	62.5	5.51*	0.129
	made healthcare harder to access	0.125	51.4	40.8	53.0	2.53	< 0.001

Capital (weight)	Indicator: household reports that displacement or hazards…	Weight	All (%)	Never displaced (%)	Ever displaced (%)	χ^2 (1 df)	Trend p
Social (1/4)	made community and social networks harder to access	0.250	19.5	20.4	19.4	0.03	0.294
Deprivation score c_i, mean			0.580	0.397	0.608		< 0.001[1]

* Trend p from a logistic regression of each indicator on the four-level exposure score. [1] Kruskal–Wallis H(3) = 60.16 across the four exposure levels; Kendall's τ-b = 0.28. *p < 0.05, **p < 0.01, ***p < 0.001.

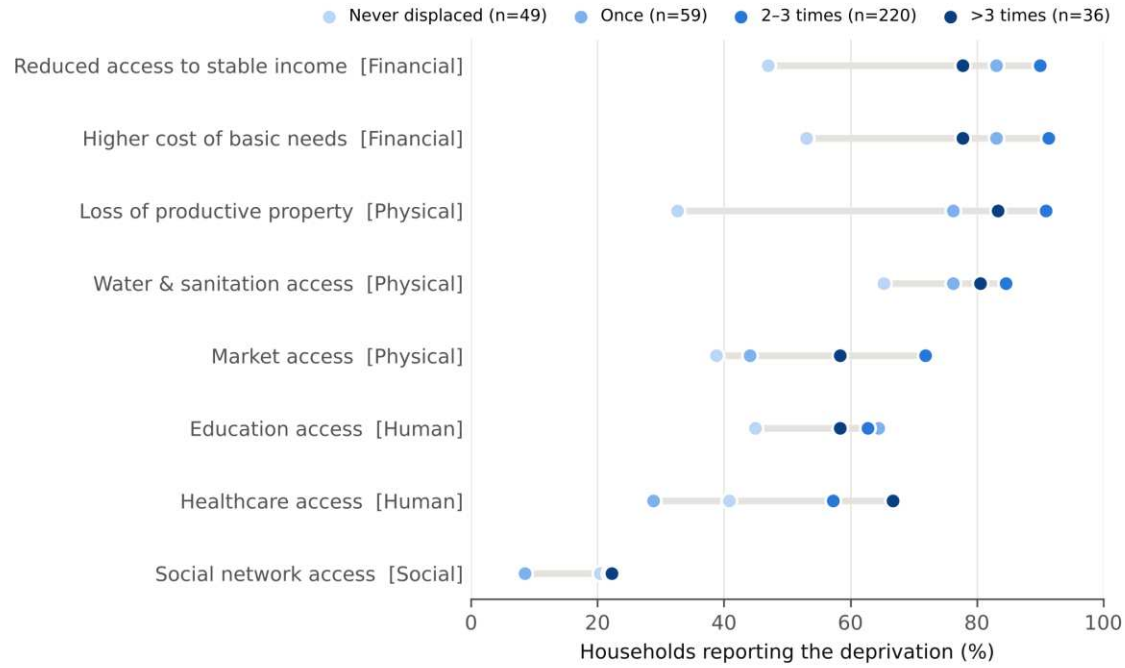


Fig. 3. Share of households reporting each deprivation, by number of displacements in the past five years (N = 364). Bracketed labels give the livelihood capital to which each indicator is assigned; the grey bar spans the range across exposure groups.

Deprivations clustered within households. The three core financial and physical losses were moderately correlated (φ = 0.37–0.48), and 67.6% of households experienced all three, against

54.7% expected if the losses were independent. The excess was proportionally largest among never-displaced households, where 18.4% experienced all three against 8.1% expected. When deprivation occurs, it therefore tends to arrive in bundles rather than as isolated losses. Education and healthcare deprivations formed a second, weaker cluster ($\varphi = 0.27$), largely independent of the financial–physical bundle ($\varphi \leq 0.17$).

4.3 Multidimensional deprivation

At k = 0.50, 72.3% of households were multidimensionally deprived, with an average intensity of 0.67 and an adjusted headcount M_0 of 0.485 (Table 3). The headcount roughly doubled between never-displaced households (40.8%) and those displaced two to three times (82.3%), then fell slightly among households displaced more than three times (77.8%). Intensity followed the same pattern. Financial capital contributed the largest share of M_0 (34.7%), followed by physical (31.5%), human (24.3%) and social capital (9.5%). Among never-displaced households, human and social capital contributed a larger share (27.4% and 16.2%), because their limited deprivation was concentrated in service access rather than in income and assets. Farming, artisanal and other informal households had the highest headcount (88.9%), and Havedzi the lowest (57.9%).

Table 3. Alkire–Foster multidimensional livelihood deprivation (k = 0.50).

Group	n	Headcount H (%)	Intensity A	M_0	Financial (%)	Physical (%)	Human (%)	Social (%)
All households	364	72.3	0.672	0.485	34.7	31.5	24.3	9.5
Displacement frequency								
Never	49	40.8	0.617	0.252	31.4	25.0	27.4	16.2
Once	59	57.6	0.598	0.345	39.3	33.6	22.1	4.9
2–3 times	220	82.3	0.693	0.570	34.5	32.0	23.9	9.6
More than 3 times	36	77.8	0.664	0.516	33.6	30.0	26.9	9.4
Main livelihood								
Fishing	143	72.0	0.644	0.464				
Trading	98	65.3	0.673	0.440				

Group	n	Headcount H (%)	Intensity A	M_0	Financial (%)	Physical (%)	Human (%)	Social (%)
Farming, artisanal and other	63	88.9	0.709	0.630				
Formal employment	60	66.7	0.689	0.459				
Community								
Keta	191	70.2	0.690	0.484				
Anyako	117	78.6	0.648	0.509				
Havedzi	38	57.9	0.670	0.388				
Seva	18	83.3	0.661	0.551				

*$M_0 = H \times A$. Capital columns give the percentage contribution of each capital to M_0; contributions sum to 100 within each row.

Source: Field data, 2026

The ranking of exposure groups was largely stable across cut-offs (Fig. 4). Households displaced two to three times had the highest headcount at every k from 0.25 to 0.75. Never-displaced households had the lowest headcount at every cut-off up to $k = 0.60$; at $k = 0.75$, never- and once-displaced households were indistinguishable (6.1% vs 5.1%). The gap between once-displaced households and those displaced two or more times widened at $k \geq 0.50$, indicating that repeated displacement is associated mainly with more severe deprivation, not only with more widespread deprivation.

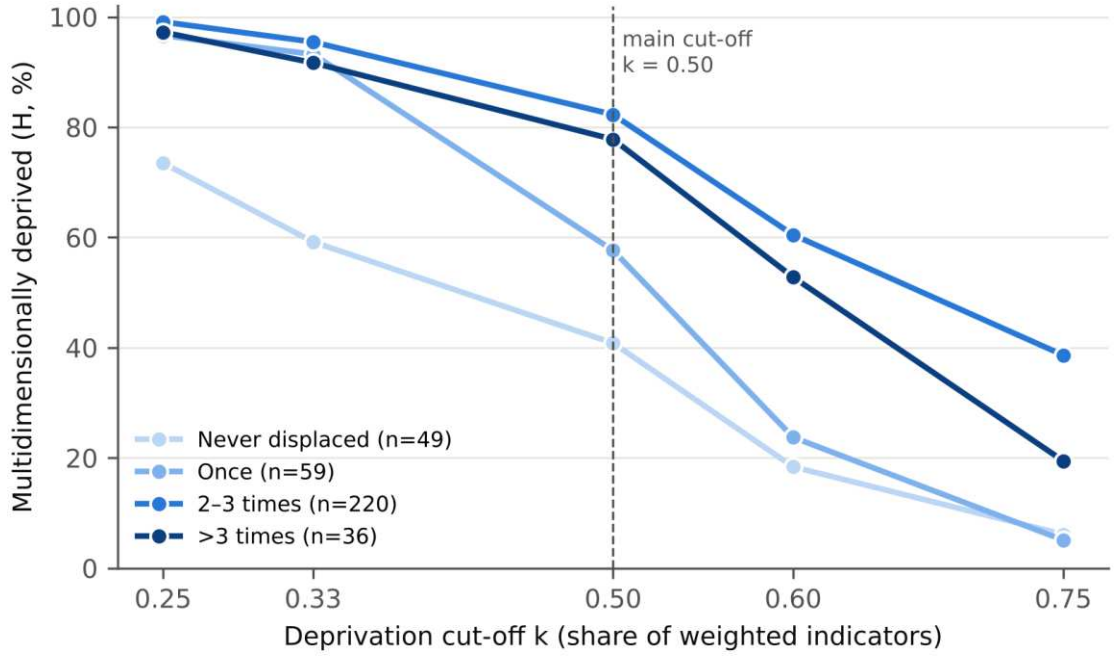


Fig. 4. Sensitivity of the Alkire–Foster multidimensional headcount (H) to the deprivation cut-off k, by displacement frequency. The dashed line marks the main cut-off (k = 0.50).

Source: Field data, 2026

4.4 Dose–response: early saturation rather than a ratchet (H1a, H1b)

After adjustment, the predicted deprivation score was 0.40 (95% CI 0.34–0.46) for never-displaced households, 0.52 (0.48–0.55) after one displacement, 0.63 (0.61–0.66) after two to three displacements and 0.61 (0.55–0.66) after more than three (Table 4; Fig. 5a). The first two steps were each significant and of similar size: +0.12 (0.05–0.19) from never to once, and +0.12 (0.07–0.16) from once to two to three. The final step was small and not significant (−0.03, −0.09 to 0.03; $p = 0.40$). The three displaced levels differed jointly (Wald $\chi^2(2) = 25.46$, $p < 0.001$), reflecting the rise from one to two or three episodes rather than further increases.

The count and AF models gave the same picture. Displaced households experienced 36% more deprivations after one displacement (IRR 1.36), 63% more after two to three (IRR 1.63) and 55% more after more than three (IRR 1.55). The odds of multidimensional deprivation were 6.4 times higher after two to three displacements and 5.7 times higher after more than three, whereas the once-displaced estimate was positive but imprecise (OR 2.16, $p = 0.085$). Overall, the data reject a strict cumulative ratchet (H1a). Deprivation rises over the first two to three displacements and then plateaus, which is consistent with early saturation (H1b), with saturation reached after the second episode rather than the first.

Among covariates, only livelihood and community were associated with deprivation. Farming, artisanal and other informal households had higher deprivation than fishing households (fractional logit $\beta = 0.47$, $p < 0.001$; IRR 1.17; OR 4.29). Havedzi households had lower odds of

multidimensional deprivation than Anyako households (OR 0.22, p = 0.002). Sex, age, education, household size, length of residence and disability were not significant in any model.

Table 4. Adjusted associations between displacement frequency and livelihood deprivation.

	(1) Deprivation score, fractional logit		**(2) Deprivation count, Poisson**	**(3) Multidimensionally deprived (k = 0.50), logit**
	Predicted mean [95% CI]	**AME vs never [95% CI]**	**IRR [95% CI]**	**OR [95% CI]**
Never displaced (ref.)	0.400 [0.344, 0.461]	—	1.00	1.00
Once	0.517 [0.480, 0.554]	0.118 [0.046, 0.185]**	1.36 [1.16, 1.60]***	2.16 [0.90, 5.18]
2–3 times	0.633 [0.608, 0.655]	0.233 [0.165, 0.294]***	1.63 [1.41, 1.89]***	6.39 [3.03, 13.46]***
More than 3 times	0.606 [0.547, 0.661]	0.206 [0.117, 0.285]***	1.55 [1.30, 1.84]***	5.69 [2.00, 16.20]**
Step contrasts (AME)				
Once − never		0.118 [0.046, 0.185]**		
2–3 − once		0.115 [0.070, 0.158]***		
>3 − 2–3		−0.027 [−0.089, 0.033]		
Selected covariates (coefficients)				
Trading (ref. fishing)	β = 0.12 (p = 0.286)		1.04 [0.96, 1.13]	0.88 [0.46, 1.70]
Formal employment	β = 0.08 (p = 0.615)		1.01 [0.90, 1.14]	1.13 [0.47, 2.71]

	(1) Deprivation score, fractional logit	(2) Deprivation count, Poisson	(3) Multidimensionally deprived (k = 0.50), logit
Farming, artisanal and other	β = 0.47 (p < 0.001)	1.17 [1.08, 1.26]***	4.29 [1.69, 10.92]**
Havedzi (ref. Anyako)	β = −0.28 (p = 0.084)	0.89 [0.78, 1.01]	0.22 [0.08, 0.59]**
Model statistics	Wald $\chi^2(2)$, displaced levels equal = 25.46***	Pearson dispersion = 0.42	LR $\chi^2(15)$ = 65.56***; McFadden R^2 = 0.152; AUC = 0.762

* N = 364. All models adjust for sex, age, education, household size, years of residence, disability, livelihood and community, with HC1 robust standard errors. AME = average marginal effect on the 0–1 deprivation score. CIs for predicted means and AMEs are from 2,000 parametric simulations. **p < 0.01, ***p < 0.001.

Source: Field data, 2026

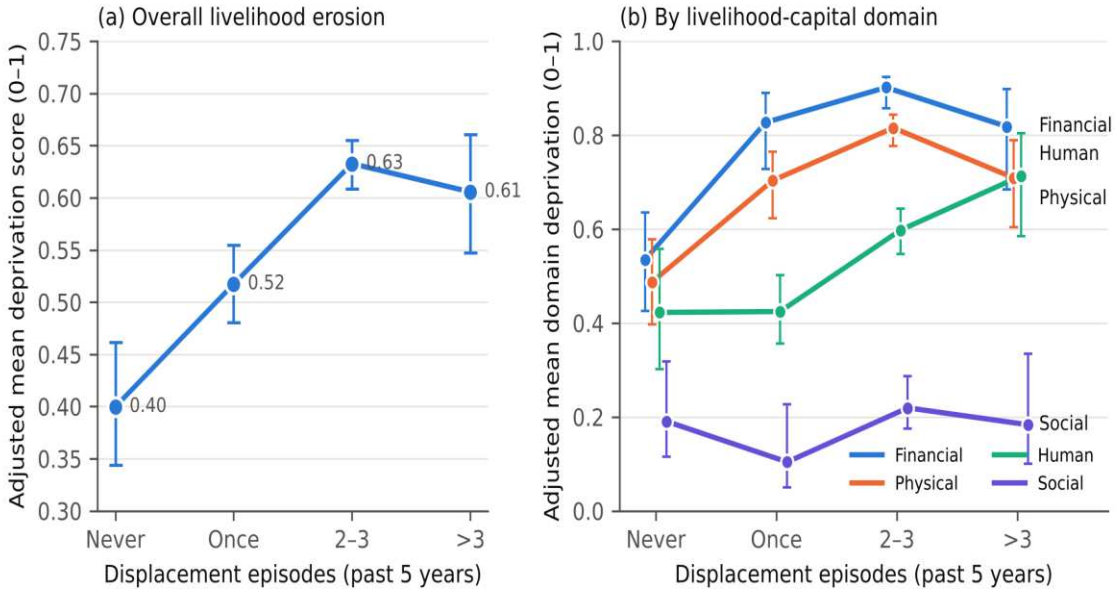


Fig. 5. Adjusted dose–response relationships. (a) Predicted deprivation score by displacement frequency. (b) Predicted capital-specific deprivation. Estimates are from fractional logit models adjusted for the covariates in Table 4; error bars are 95% simulation confidence intervals.

Source: Field data, 2026

4.5 Sequenced erosion across capitals (RQ2)

The capital-specific models show that the plateau in the overall score hides two distinct trajectories (Table 5; Fig. 5b). Financial and physical deprivation rose steeply with the first displacement (+0.29 and +0.22, respectively), peaked at two to three displacements and showed no further trend among displaced households (trend p = 0.675 and 0.223). Most of the financial and physical damage was therefore done by the first one or two episodes.

Human-capital deprivation followed a different path. One displacement had no association with access to education and healthcare (AME +0.00, −0.15 to 0.14). The effect appeared after two to three displacements (+0.18, 0.03 to 0.30) and was largest after more than three (+0.29, 0.10 to 0.44), with a significant linear trend among displaced households (β = 0.74, p < 0.001). The predicted human-capital score rose from 0.42 among never- and once-displaced households to 0.71 among the most frequently displaced, the only capital still rising at the top of the exposure range. Social-capital deprivation was unrelated to displacement at any level.

Table 5. Average marginal effects of displacement frequency on capital-specific deprivation (fractional logit; reference = never displaced).

Capital	Predicted mean, never	Once	2–3 times	More than 3 times	Trend among displaced, β (p)
Financial	0.535	0.292 [0.152, 0.412]	0.366 [0.253, 0.472]	0.283 [0.107, 0.418]	0.14 (0.675)
Physical	0.487	0.216 [0.092, 0.322]	0.328 [0.227, 0.418]	0.221 [0.084, 0.346]	0.23 (0.223)
Human	0.422	0.002 [−0.153, 0.145]	0.175 [0.027, 0.298]	0.291 [0.105, 0.444]	0.74 (< 0.001)
Social	0.190	−0.086 [−0.224, 0.063]	0.029 [−0.100, 0.128]	−0.007 [−0.161, 0.151]	0.34 (0.196)

Note: Values are AMEs with 95% simulation CIs. Covariates as in Table 4. Trend β is the coefficient on the 1–3 exposure score in a fractional logit restricted to displaced households (n = 315).

Source: Field data, 2026

Qualitative accounts help explain this sequencing. Participants described the first displacement as the moment when productive assets and daily earnings were lost together. Human-capital losses, in contrast, were described as the result of repeated depletion:

> *People lost nets and other fishing gear when the waters hit. Then, after they found shelter, it was hard to get money to buy those things back* **(FGD, male, Seva).**
>
> *Relocation creates many small expenses that eventually become a big burden. You pay for transportation, food, water and sometimes rent* **(FGD, female, Seva).**
>
> *Many households struggle to rebuild their livelihoods after each flood, keeping them in a cycle of poverty* **(KII, NADMO officer).**
>
> *Paying for rent, healthcare, and school fees is impossible due to economic instability.* **(Social Welfare Officer).**

4.6 Does formal employment buffer displacement? (H2)

Formal employment lowered overall deprivation only among households that had not been displaced (interaction model; Section 3.4, Step 4). Among never-displaced households, the predicted score was 0.32 (0.21–0.45) for formally employed households and 0.42 (0.35–0.49) for place-dependent households. Among displaced households, the two groups converged (0.60 vs 0.61). The displacement effect was therefore at least as large for formal households (+0.28, 0.14 to 0.40) as for place-dependent ones (+0.20, 0.12 to 0.26). The difference was not significant (−0.09, −0.23 to 0.08; $p = 0.29$), so H2 is not supported. Formal employment improved a household's baseline position, but it did not protect against displacement once it occurred.

Disaggregating the score shows why the composites converge. Among displaced households, formally employed households ($n = 49$) were less likely than place-dependent households ($n = 266$) to report reduced income (71.4% vs 90.2%), higher basic-needs costs (79.6% vs 89.8%) and property loss (73.5% vs 89.8%). However, they were more likely to report difficulty accessing education (71.4% vs 60.9%) and healthcare (65.3% vs 50.8%). Formal employment thus protects financial and physical capital but not access to services, which displacement itself erodes.

As one participant put it, *"when the floods come, my salary still comes at the end of the month, but my neighbours who sell at the market lose everything for weeks"* (FGD, female, Anyako). A regular wage protects income, but it does not keep a school or clinic within reach of a displaced household. These subgroup contrasts are descriptive and rest on a small formal subsample.

4.7 Robustness

The dose–response shape was stable across all specifications (Table 6). The AMEs for once, two to three, and more than three displacements maintained the same ordering, with the two-to-three level highest, under equal indicator weights, OLS, excluding Seva, and adding income and prior

relocation. Adding the potential mediators left the AMEs essentially unchanged (differences ≤ 0.024), suggesting that the association does not operate mainly through current income. The ordered logit of the deprivation count gave the same peak at two to three displacements (OR 15.9). A modified Poisson model estimated a risk ratio of 1.84 (1.31–2.58) for multidimensional deprivation among ever-displaced households. The corresponding E-value of 3.08 (lower CI 1.94) means that, beyond the measured covariates, an unmeasured confounder would need to be associated with both displacement and deprivation by a risk ratio of at least 3.1 to fully explain away the association.

Table 6. Robustness of the displacement–deprivation gradient (AMEs vs never displaced unless stated).

Specification	Once	2–3 times	More than 3 times
Main model (Table 4, col. 1)	0.118 [0.046, 0.185]	0.233 [0.165, 0.294]	0.206 [0.117, 0.285]
R1. Equal indicator weights	0.153 [0.075, 0.224]	0.270 [0.201, 0.334]	0.235 [0.142, 0.318]
R2. + log income and prior relocation	0.142 [0.070, 0.212]	0.239 [0.172, 0.301]	0.209 [0.122, 0.284]
R3. OLS, HC3 errors ($R^2 = 0.233$)	0.118 [0.042, 0.193]	0.233 [0.164, 0.302]	0.206 [0.114, 0.298]
R4. Excluding Seva (n = 346)	0.115 [0.045, 0.182]	0.237 [0.171, 0.298]	0.203 [0.121, 0.274]
R5. Ordered logit of count, OR	4.48 [2.11, 9.49]	15.89 [8.02, 31.48]	11.14 [4.65, 26.70]
R6. AF cut-off k = 0.25–0.75	2–3 times highest at every k; never displaced lowest at every k ≤ 0.60 (Fig. 4)		
R7. Modified Poisson, ever displaced	RR = 1.84 [1.31, 2.58]; E-value = 3.08 (CI bound 1.94)		

* R4 excludes Seva and omits community fixed effects; all other specifications use the full covariate set of Table 4.

5. Discussion

5.1 Saturation, not a steady ratchet

The central finding is that livelihood deprivation in Keta rises steeply over the first two to three displacements and then levels off. This is neither the linear accumulation implied by a simple ratchet nor saturation at the very first event. Rather, the overall score climbs in two roughly equal steps and plateaus at about 0.6. This pattern matters for how poverty-trap reasoning is applied to recurrent displacement. Asset-based models predict that repeated shocks push households below a threshold from which they cannot recover (Carter & Barrett, 2006; Carter et al., 2007). Our results are consistent with crossing such a threshold early, after the second episode, beyond which the measured indicators have little room to deteriorate further. In a population where 87% of displaced households have already lost access to income and productive property, the indicators approach a ceiling.

Two further mechanisms may contribute to the plateau. First, households that stay through more than three displacements are a selected group. Those who could leave may already have done so, while those who remain may be bound by place attachment, livelihood ties to the shore or a lack of resources to move (Adams, 2016; Black et al., 2013; Zickgraf, 2018). A NADMO officer described this directly: *"Most fishermen do not want to move very far away just because of their livelihood. Their living is at the coast."* Second, households exposed most often may develop routinised coping practices, such as moving valuables, shifting to temporary structures, or pre-arranging shelter with kin, that limit marginal losses from each new episode. The cross-sectional design cannot separate these explanations. However, it does show that counting displacements beyond the third adds little information about current deprivation, whereas the transition from none to two or three is decisive.

The plateau should not be read as recovery. At a predicted score of 0.61, the most frequently displaced households remain deprived in well over half of their weighted livelihood indicators, and 78% are multidimensionally deprived. Saturation describes a persistently high level of deprivation, not an improvement.

5.2 Capitals erode in sequence

Disaggregation reveals that the plateau combines two different trajectories. Financial and physical capitals respond almost entirely to the first one or two displacements. This fits the mechanics of coastal flooding: water destroys nets, canoes, stock and buildings directly, and fishing and trading income stops while households are displaced (Hallegatte et al., 2017; Warner and van der Geest, 2013). These are front-loaded losses.

Human-capital deprivation, by contrast, shows no response to a single displacement but rises steadily with repetition, and it is the only capital still increasing at the highest exposure level. This is consistent with evidence that the human-capital effects of shocks emerge as household buffers are depleted and can persist long after the shock itself (Hoddinott, 2006; Dercon, 2004). Repeated relocation also moves households farther from schools and clinics, and the costs of transport, fees, and lost days accumulate. Human-capital losses are therefore *back-loaded* and have the longest consequences, because interrupted schooling and deferred health care shape a household's prospects long after the water has gone (Tschakert et al., 2019).

To our knowledge, this sequencing has not been documented for climate-induced displacement. It refines the SLF's treatment of capitals as an interdependent portfolio (Bebbington, 1999; Scoones, 2009) by adding a temporal order: in this setting, depletion runs from financial and physical capitals to human capital as displacement recurs. It also supports the systemic-risk argument that losses cascade across connected systems (Renn et al., 2022), showing that the cascade unfolds across episodes and sectors.

The absence of a social-capital effect deserves comment. Fewer than one in five households reported losing access to community networks, and this did not vary with exposure. In Keta's dense, kin-based settlements, displacement is often short-distance, and households shelter with relatives nearby. Social networks may therefore act as the main buffer that remains intact while other capitals erode, a role also noted in research on livelihood resilience in coastal Bangladesh (Ayeb-Karlsson et al., 2016). Social capital in the study index is measured by a single item, however, so this conclusion is tentative.

5.3 Spillovers and the limits of occupational buffering

Two further results qualify the common picture of who is affected. First, never-displaced households were far from untouched: their mean score was 0.40, nearly half reported reduced income, and 65% reported difficulty accessing water and sanitation. Because the survey items referred to displacement and hazard effects, this indicates community-wide spillovers. When markets, schools, and water points in a settlement flood, households whose homes remain dry still lose access to them. Assessments that compare displaced with non-displaced households therefore understate the total livelihood burden of displacement events.

Second, formal employment did not buffer the displacement effect as a whole. Formal households started from a lower baseline when not displaced and, after displacement, were less likely than place-dependent households to report reduced income (71.4% vs 90.2%) or property loss (73.5% vs 89.8%). Yet they reported more difficulty reaching schools and health services, and their overall deprivation converged with that of their neighbours. The protective role commonly attributed to livelihood diversification (Adger, 2006; Cutter et al., 2003) therefore operates within the financial domain. A secure salary does not prevent the loss of a home or of local services, both of which are tied to place rather than to occupation. The higher deprivation of farming, artisanal and other informal households, which are often the least capitalised and most dependent on local customers, reinforces this reading.

5.4 Implications for policy and practice

The results point to three changes in how support is designed and timed in Keta and similar coastal settings.

1. Because financial and physical losses saturate within the first one or two displacements, the most effective window for support is the first episode. Rapid replacement of fishing gear, stock and working capital, through cash transfers or in-kind grants channelled via NADMO and the Department of Social Welfare, could prevent households from crossing

the threshold observed here. Hallegatte et al. (2017) argue that rapid, scalable post-disaster support, including cash transfers, reduces poor households' long-term losses.

2. Since education and health deprivation accumulates with repetition, households displaced more than once should be prioritised for fee waivers, school feeding, transport support and continuity of enrolment in the National Health Insurance Scheme. Displacement frequency, which is easy to record, could serve as a targeting criterion.
3. Spillovers to non-displaced households mean that flood-proofing shared infrastructure (water points, markets, schools and clinics) benefits whole settlements. This links household-level displacement to the municipality's investment in coastal defence and to the priorities of the Sendai Framework (UNDRR, 2015).

6. Conclusion

This study aimed to determine whether recurrent climate-induced displacement erodes livelihoods cumulatively and whether all livelihood capitals erode at the same pace. In four tidal-flood and erosion hotspots in Keta Municipality, livelihood deprivation rose steeply over the first two to three displacements and then levelled off at a persistently high level. Households depleted financial and physical capital early, while losses in access to education and healthcare accumulated with each subsequent episode. Formal employment protected income and assets but not access to services, and households that had never been displaced still bore part of the burden through community-wide disruption.

Treating displacement as a binary event obscures both the timing and the sequence of these losses. For coastal West Africa, where tidal flooding and shoreline retreat are expected to intensify (Trisos et al., 2022), the results argue for support that arrives at the first displacement to protect assets and income, combined with sustained protection of schooling and health care for households that are displaced repeatedly. Measuring how often households are displaced, not just whether they are, is a simple and effective step toward that goal.

References

Adams, H. (2016). Why populations persist: mobility, place attachment and climate change. *Population and Environment*, *37*(4), 429-448.

Addo, K. A., Nicholls, R. J., Codjoe, S. N. A., & Abu, M. (2018). A biophysical and socioeconomic review of the Volta Delta, Ghana. *Journal of Coastal Research*, *34*(5), 1216-1226.

Adger, W. N. (2006). Vulnerability. *Global environmental change*, *16*(3), 268-281.

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of public economics*, *95*(7-8), 476-487.

Alkire, S., & Santos, M. E. (2014). Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. *World development*, *59*, 251-274.

Appeaning Addo, K., Jayson-Quashigah, P. N., Codjoe, S. N. A., & Martey, F. (2018). Drone as a tool for coastal flood monitoring in the Volta Delta, Ghana. *Geoenvironmental Disasters*, *5*(1), 17.

Ayeb-Karlsson, S., Van der Geest, K., Ahmed, I., Huq, S., & Warner, K. (2016). A people-centred perspective on climate change, environmental stress, and livelihood resilience in Bangladesh. *Sustainability Science*, *11*(4), 679-694.

Bebbington, A. (1999). Capitals and capabilities: a framework for analyzing peasant viability, rural livelihoods and poverty. *World development*, *27*(12), 2021-2044.

Black, R., Arnell, N. W., Adger, W. N., Thomas, D., & Geddes, A. (2013). Migration, immobility and displacement outcomes following extreme events. *Environmental Science & Policy*, *27*, S32-S43.

Boateng, I. (2012). An application of GIS and coastal geomorphology for large scale assessment of coastal erosion and management: a case study of Ghana. *Journal of coastal conservation*, *16*(3), 383-397.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology*, *3*(2), 77-101.

Carter, M. R., & Barrett, C. B. (2006). The economics of poverty traps and persistent poverty: An asset-based approach. *The Journal of Development Studies, 42*(2), 178–199.

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2007). Poverty traps and natural disasters in Ethiopia and Honduras. *World development*, *35*(5), 835-856.

Cochran, W. G., & Cochran, W. G. (1977). *Sampling techniques* (Vol. 3, No. 4, pp. 2584-1807). New York: wiley.

Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly, 84*(2), 242–261.

Dercon, S. (2004). Growth and shocks: evidence from rural Ethiopia. *Journal of Development economics*, *74*(2), 309-329.

DfID, U. K. (1999). Sustainable livelihoods guidance sheets. *London: DFID*, *445*, 710.

Ghana Statistical Service. (2021). Ghana 2021 population and housing census. *General Report*, *3*.

Hallegatte, S., Vogt-Schilb, A., Bangalore, M., & Rozenberg, J. (2017). *Unbreakable: Building the resilience of the poor in the face of natural disasters*. World Bank.

Hoddinott, J. (2006). Shocks and their consequences across and within households in rural Zimbabwe. *The Journal of Development Studies, 42*(2), 301–321.

Internal Displacement Monitoring Centre. (2025). *Global report on internal displacement 2025*. IDMC.

Jayson-Quashigah, P. N., Appeaning Addo, K., & Kufogbe, S. K. (2013). Medium resolution satellite imagery as a tool for monitoring shoreline change: Case study of the Eastern coast of Ghana. *Journal of Coastal Research, SI 65*, 511–516.

Mechler, R., Bouwer, L. M., Schinko, T., Surminski, S., & Linnerooth-Bayer, J. (2019). *Loss and damage from climate change: Concepts, methods and policy options* (p. 557). Springer Nature.

Mortreux, C., & Barnett, J. (2009). Climate change, migration and adaptation in Funafuti, Tuvalu. *Global environmental change*, *19*(1), 105-112.

Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of applied econometrics*, *11*(6), 619-632.

Renn, O., Laubichler, M., Lucas, K., Kröger, W., Schanze, J., Scholz, R. W., & Schweizer, P. J. (2022). Systemic risks from different perspectives. *Risk analysis*, *42*(9), 1902-1920.

Scoones, I. (1998). Sustainable rural livelihoods: a framework for analysis.

Scoones, I. (2009). Livelihoods perspectives and rural development. *The journal of peasant studies*, *36*(1), 171-196.

Trisos, C. H., Adelekan, I. O., Totin, E., Ayanlade, A., Efitre, J., Gemeda, A., Kalaba, K., Lennard, C., Masao, C., Mgaya, Y., Ngaruiya, G., Olago, D., Simpson, N. P., & Zakieldeen, S. (2022). Africa. In H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama (Eds.), *Climate change 2022: Impacts, adaptation and vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1285–1455). Cambridge University Pres

Tschakert, P., Ellis, N. R., Anderson, C., Kelly, A., & Obeng, J. (2019). One thousand ways to experience loss: A systematic analysis of climate-related intangible harm from around the world. *Global Environmental Change*, *55*, 58-72.

Tumawu, A. F., Kafu, G. Y., Yiran, G. A. B., & Frimpong, L. K. (2024). Assessment of coastal flood risk scenarios on infrastructure in the Keta municipality in Ghana using a GIS approach. *Heliyon*, *10*(21).

United Nations Office for Disaster Risk Reduction. (2015). *Sendai framework for disaster risk reduction 2015–2030*. UNDRR.

VanderWeele, T. J., & Ding, P. (2017). Sensitivity analysis in observational research: introducing the E-value. *Annals of internal medicine*, *167*(4), 268-274.

Warner, K., & Van der Geest, K. (2013). Loss and damage from climate change: local-level evidence from nine vulnerable countries. *International Journal of Global Warming*, *5*(4), 367-386.

Williams, R. (2012). Using the margins command to estimate and interpret adjusted predictions and marginal effects. *The Stata Journal*, *12*(2), 308-331.

Zickgraf, C. (2018). Immobility. In *Routledge handbook of environmental displacement and migration* (pp. 71-84). Routledge.

Zou, G. (2004). A modified poisson regression approach to prospective studies with binary data. *American journal of epidemiology*, *159*(7), 702-706.