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Environmental change and migration aspirations: Evidence from Bangladesh

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A B S T R A C T

The argument that environmental stress is an important driver of migration has gained renewed attention amidst increasing climatic changes. This study examines whether and how two distinct environmental stressors influence migration aspirations among affected populations. Our analysis relies on two waves of original survey data of 1,594 households residing in 36 villages along the 250 km of the Jamuna River in Bangladesh, an area heavily impacted by floods and riverbank erosion. The results reveal that riverbank erosion – a long-term environmental event causing permanent destruction – increases aspirations for internal, permanent migration by about 15 percentage points, 4 to 6 months after the occurrence. In contrast, sudden and short-term events, like floods, which have a more temporary impact, do not affect migration aspirations. These results suggest that the type of environmental event shapes adaptation strategies, with migration emerging as a viable response to more severe and lasting events such as erosion. This entails important policy implications regarding the effects of climate change on future patterns of internal migration and highlights that most affected individuals prefer to adapt to environmental stress *in situ* or within close proximity.

1. Introduction

Climate change is expected to increase the frequency and intensity of climate events such as storms, floods, and droughts and contributes to sea level rise (IPCC, 2021). In turn, these climatic changes may increase migration flows, especially of vulnerable people (Foresight, 2011). According to the World Bank's latest *Groundswell* report, under a business-as-usual scenario (i.e., high greenhouse gas emissions and unequal development), slow-onset climatic changes could force 216 million people in six regions of the world (of which 13.5 million reside in Bangladesh) to move by 2050 to escape the impacts of climate change (Clement et al., 2021). Furthermore, there is sufficient evidence to claim that climate-related events make it more likely that people migrate primarily within their own country (e.g., Afifi et al., 2016; Clement et al., 2021; Foresight, 2011). Yet, this effect does not hold under all circumstances, and a significant amount of variation persists in migration (or non-migration) patterns of people affected by the same climate event, such as a drought or a flood (Koubi et al., 2022; Thiede et al., 2016). It thus remains not well understood whether and how environmental factors shape individuals' decisions to migrate (Black et al., 2011; Cattaneo et al., 2019; Koubi, Spilker, et al., 2016).

In this study, we aim to enhance our understanding of environmental migration by examining whether and how environmental stress influences people's perception of migration as desirable or necessary – essentially, their *migration aspirations* (Carling & Schewel, 2018, p. 946). As climate change intensifies, environmental stress is expected to significantly impact the livelihoods of many people in rural Bangladesh and beyond, potentially leading to higher internal migration rates, particularly towards urban centers (Kumari Rigaud et al., 2018). However, this trend is not uniform; there is considerable variation in migration patterns even among individuals experiencing the same climate event (Cattaneo et al., 2019). To better understand these dynamics, we need to examine whether people affected by environmental or climate-related factors aspire to and are able to move based on the aspirations-capabilities framework proposed by Carling & Schewel (2018) and de Haas (2021). Aspirations refer to individuals' potential migration based on their thoughts and feelings rather than their actual migration behavior, which is influenced by their capacity/ability to turn these psychological elements into actions (Carling & Collins, 2018; Carling & Schewel, 2018). While the extent to which migration aspirations reflect actual behavior versus wishful thinking is debated, studies show that migration intentions often predict future migration (e.g.,

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Docquier et al., 2014; Kang et al., 2007; Tjaden et al., 2019; van Hear et al., 2018; Williams et al., 2018), supporting the theory of planned behavior that expectations and intentions are central drivers of actions (Ajzen, 1991).

Migration aspirations "can take a variety of forms, from lifestyle-driven preferences to urgencies to escape danger, with innumerable possibilities in between" (Carling & Schewel, 2018, p. 959). This suggests that some individuals aspire to migrate because of the intrinsic value they place on the migration experience itself, such as the joy and pleasure derived from exploring new places (intrinsic aspirations). Others, however, seek migration as a means to achieve practical goals, such as higher income, social status, or better education, or to mitigate threats to their livelihood emanating from, e.g., environmental changes (instrumental aspirations) (Carling & Schewel, 2018; de Haas, 2021). In the extant literature, *migration aspirations* are mainly conceived as a means to an end, and consequently, they tend to refer to the basic conviction that leaving a particular place would be better than staying (Carling & Schewel, 2018, p. 946).[1] In the context of environmental changes, we conceive migration aspirations "as urgencies to escape danger" (Carling & Schewel, 2018, p. 959). This 'urgency to escape danger' develops when environmental changes have a major impact on people's livelihoods (Birkmann et al., 2022), and people's efforts to mitigate and/or adapt *in situ* to this impact have failed or are likely to fail in the future (Penning-Rowsell et al., 2013).

Not everyone perceives the 'urgency to escape danger' from environmental changes similarly. For example, farmers and fishermen are more vulnerable to droughts and floods than civil servants, meaning they may have a higher likelihood of migration aspirations than the latter. This implies that individuals' migration aspirations are strongly affected by their vulnerability to environmental changes, which is linked to how people perceive these events to impact their livelihoods (Carling & Schewel, 2018; Zickgraf, 2018).

We argue that different types of environmental changes, in particular sudden/short-term and gradual/long-term environmental events, affect migration aspirations in diverse ways (Black et al., 2013; Cattaneo et al., 2019; Koubi et al., 2022; Koubi, Spilker, et al., 2016; Koubi, Stoll, & Spilker, 2016; McLeman, 2014). However, this classification of environmental events is based solely on the speed of onset (sudden- versus gradual onset) and duration (short- versus long-term) of the events, without considering the specific impact these events have on affected households. Consequently, we argue that migration aspirations of affected individuals/households depend also on the nature of the impact, that is, whether the impact caused by the specific environmental event is reversible or irreversible.

Sudden/short-term environmental events, such as floods and storms, can have severe, immediate impacts on the well-being of individuals by inflicting injuries and casualties, causing property damage, food insecurity, or economic disruption (Wallemacq & House, 2018). These events are thus easily recognizable as extreme, and people might consider moving away from the affected areas (Warner, 2010, p. 405). Indeed, the IDMC (2019) reports that an average of 24 million people a year fled their homes during the 2008–2018 period due to disasters, with 98% of those caused by floods and storms. Moreover, the emerging literature on environmental migration suggests that most migration in the aftermath of sudden environmental events tends to be short-distance and short-duration (Cattaneo et al., 2019; Curtis et al., 2015), especially among individuals who struggle to secure a stable income (Saha, 2017). Furthermore, the majority of those who moved away tend to return as soon as possible to rebuild their homes and livelihoods (Cattaneo et al., 2019). Consequently, we argue that in the presence of sudden/short-term events, people aspire to migrate only temporarily, as the impacts of these events are generally reversible. We thus expect the 'aspiration to migrate' following floods to be high for internal, temporary moves.[2]

Gradual/long-term events, such as coastal/riverbank erosion, soil and water salinity, and sea level rise, are typically not perceived as extreme due to their slow-moving nature, and hence, they tend to remain beneath the perceptual threshold of immediate risk (Howe et al., 2013) that would trigger a need to move, even though their economic impact can be significant (Chen et al., 2022). In these cases, people might be more willing to implement alternative adaptation or mitigation strategies (Koubi et al., 2022). For instance, in Bangladesh, people plant water-resistant rice varieties and horticultural crops in response to droughts (Al-Amin et al., 2019) and build bamboo or sandbag walls to protect riverbanks from erosion (Mamun et al., 2022). However, when these events unfold, their impacts are usually irreversible, resulting in the complete and permanent destruction of agricultural land, homes, and infrastructure. Consequently, we expect that people affected by such events will likely develop long-term aspirations to migrate permanently and potentially long-distance, as they have lost their physical attachment to the land and must compensate for the losses.

Empirically, we base our analysis on an extensively pre-registered (see Appendix C) face-to-face survey (N = 1,594) conducted with populations at risk of riverbank erosion along the entire stretch of the Jamuna River in Bangladesh. To address endogeneity concerns, we carefully designed our sampling frame, collected objective and subjective exposure data, and tracked respondents who moved from their household's original location. Acknowledging that migration aspirations are also influenced by third factors, which might simultaneously relate to the experience of environmental events, we use matching techniques based on data we gathered pre-exposure to make affected and unaffected households as comparable as possible. These include socio-demographic and attitudinal variables such as gender, age, education, socio-economic status, risk attitudes, place attachment, or prior exposure. Our main finding is that migration aspirations double in response to the impacts of riverbank erosion but not floods.

Our study contributes to the existing literature in several ways. When seeking to understand how people react to environmental shocks, most existing research focuses on barriers at the destination, including skill mismatches, religion, ethnicity, distance, costs, and market distortions (Lucas, 2021). It fails to consider whether climate-affected individuals actually want to move in the first place. It is, however, crucial to examine barriers to mobility after exposure to environmental events, not just in terms of actual migration but also regarding aspirations to migrate. A growing body of research is examining drivers of migration aspirations more generally – such as individual/household characteristics (e.g., gender, age, education, and income) and local or national socioeconomic and political/institutional factors (e.g., economic development, governance, and corruption), especially in the context of international migration (e.g., Marrow & Klekowski von Koppenfels, 2020; Méndez, 2020; Migali & Scipioni, 2019; Sadiddin et al., 2019). However, to the best of our knowledge, only limited scholarly work addresses the impact of environmental stress on migration aspirations and intentions (Bertoli et al., 2021, and Helbling et al., 2021, are notable exceptions). Second, our measures for migration aspirations are more stringent than the typical migration considerations used in recent research: We directly ask respondents whether they desire to move at the time of the survey instead of whether they would (ideally) like to

[1] Other terms used include desires, wishes, expectations, and preferences (Carling & Collins, 2018; Carling & Schewel, 2018). In this study, migration aspirations refer to voluntary migration, and not to forced migration (displacement).

[2] However, it remains unclear how long these migration aspirations last, whether they persist several months after the natural disaster once the immediate environmental pressure on livelihoods has eased, and the extent to which sudden-onset climate events contribute to permanent, long-term migration aspirations. Given our research design, which observes migration aspirations 4–6 months after the flood, it remains an open empirical question whether flood occurrence actually leads to increased migration aspirations.

move permanently to another country (Bertoli et al., 2021). Furthermore, we explore additional dimensions of migration aspirations, such as the intended destination (internal versus international, rural versus urban) and the duration of stay (temporary versus permanent). Third, with our research design, we take great care to maximize our results' external and internal validity. Regarding the former, we use a GIS-based sampling approach to ensure our sample is representative of households at different levels of risk for riverbank erosion and floods along the entire 250 km of the Jamuna River in Bangladesh. Regarding the latter, our research design is tailored to exploit the natural, i.e., quasi-random, variation in erosion and flood occurrence within this population at risk, surveying respondents before and after the potential occurrence of these events.

Consequently, examining individual (self-reported) environmental impacts, which are inherently subjective, can provide valuable insights into migration aspirations, which are similarly subjective but also serve as a critical precursor to actual migration behavior in response to environmental changes. A better understanding of the formation of these aspirations is essential as it allows for assessing migration propensities in a world experiencing environmental and climatic changes, which could enhance our understanding of migrant selection and potential future migration dynamics and patterns, ultimately informing more effective policy responses.

2. Research design

To empirically examine the effect of environmental changes on migration aspirations, we use data from two waves of a high-quality, face-to-face population-representative panel survey of 1,594 river-proximate household heads residing in 36 locations distributed along the whole 250 km of the Jamuna River in Bangladesh, where all households are at risk of floods and riverbank erosion (Fig. 1).

2.1. Case: Jamuna River in Bangladesh

We chose Bangladesh because it is among the countries most susceptible to the adverse effects of climate change (Kumari Rigaud et al., 2018), owing to its topography and its location in one of the largest river deltas of the world. The country is affected heavily by sea level rise, frequent cyclones, and high monsoon rainfall that increases river flow, leading to widespread flooding and riverbank erosion (Hasan et al., 2018; Islam et al., 2021). The future intensification of these climate events (IPCC, 2021) will adversely affect people and their livelihoods, potentially driving large-scale migration, with up to 13.3 million (internal) environmental migrants by 2050 in a pessimistic scenario of high emissions and low development (Kumari Rigaud et al., 2018). In Bangladesh, riverbank erosion and floods are the most impactful processes regarding yearly damage (Ahmed, 2015).

The Jamuna River, our case study region, is one of the most dynamic river systems in the world (Oberhagemann et al., 2020). It exhibits significant spatial, temporal, and inter-household variation in both riverbank erosion and floods along its whole length (see Section A.1 in the online Appendix A). For example, the net erosion along its 250 km was about 933 km^2 during the 1973–2017 period (CEGIS, 2018), which would correspond to an inland shift of the riverbank of over four kilometers if the erosion was distributed evenly along the river. Riverbank erosion has several negative impacts on affected communities, including the destruction of farmable land, housing, and infrastructure such as

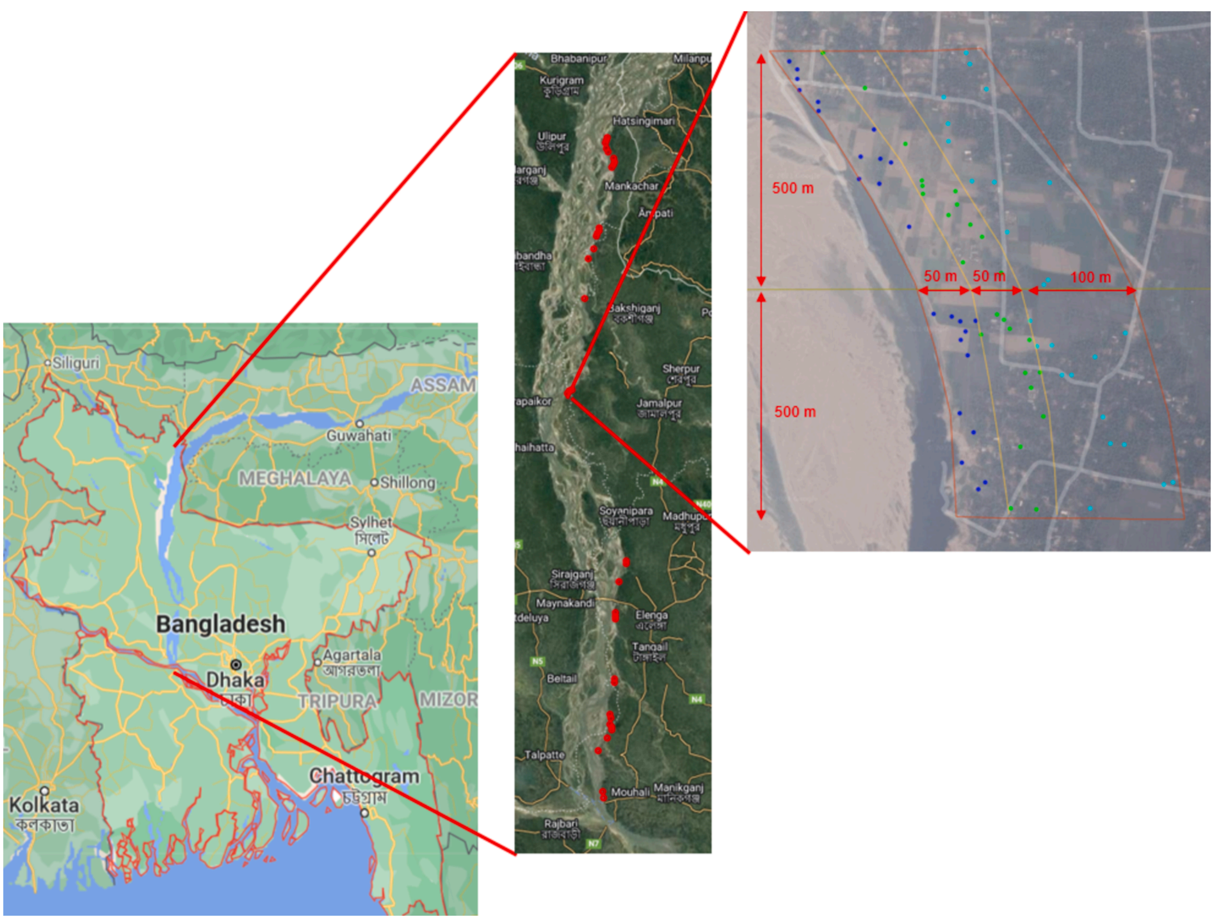

Fig. 1. ***Overview of the Jamuna River, the 36 study locations as well as the three sampling zones within each location***. Copyright map: Google. Copyright satellite images: TerraMetrics, 2022.

roads or schools. Similarly, while regular flooding is beneficial for making the land fertile for farming, severe flooding may turn into a disaster, damaging crops, houses, and infrastructure (Alam, 1990). These environmental impacts are believed to significantly shape migration patterns in the area (e.g., Alam et al., 2019; Gray & Mueller, 2012; Islam et al., 2020; Kabir et al., 2018; Khandker et al., 2012; Mallick & Vogt, 2014).

The regions we study experience significant outgoing labor migration unrelated to environmental events. However, the season in which we conducted our survey to measure migration aspirations (January-March) does not coincide with the peak for labor migration. From an agricultural perspective, the post-planting and pre-harvest season for Aman rice (September to November), locally termed the Monga season (Zug, 2006), is when labor demand is lowest in the villages (Bryan et al., 2014). During this time, we would expect migration aspirations to rise due to economic hardship. In contrast, January to February corresponds to the sowing season for Boro rice (Singha et al., 2019), when labor demand in the villages is higher. Hence, we do not expect any worrisome influence of seasonality on migration aspirations.

2.2. Survey data

We collected survey data between January and March 2022 on migration aspirations and self-reported impacts of flood and erosion exposure during the 2021 monsoon season. We also collected data on time-variant attitudes and household characteristics from the same respondents in June 2021, prior to the 2021 monsoon season (for a timeline, see Fig. A.1). Panel attrition between the two waves was less than 6% (see Appendix A1.2 for more details on attrition). The interviews, conducted face-to-face in Bangla by native interviewers, lasted approximately 45–60 minutes. The questionnaires included closed and open-ended questions about respondents' experiences with environmental events and migration, as well as personal and household information.

2.2.1. Household selection

Regarding the selection of households for our study, we employed a pre-registered, multi-stage cluster design (see Appendix Section A.2.1 for details). We identified all areas of potential flood and erosion exposure and conducted surveys in 36 locations, covering 86% of all suitable sites. At each location, households were sampled using a stratified random spatial sampling design to survey households located within three zones defined by distance from the shoreline, i.e., the cutoff line between land and the river basin. The three zones at each location were constructed by shifting the shoreline inland by 50 m (high ex-ante risk of erosion), 100 m (medium risk), and 200 m (low risk). Consequently, each sampling area has an overall extent of 200 m inland and 1 km along the flow direction.

Within each of the three zones, we generated a spatially explicit sample using the procedure outlined by Crawford et al. (2020). In particular, we generated 25 random latitude-longitude points per zone using ArcMap software, ensuring a minimum distance of 10 m between points. In the field, enumerators navigated to these points using smartphones. Upon reaching each point, they selected the nearest house based on visual estimation and conducted the interview. If the household declined participation or the household head was unavailable after two contact attempts, the enumerator moved to the next closest household in reference to the starting point. Within each household, the household head, defined as the primary decision-maker, was interviewed. This approach ensured that our sample is representative of *all households* at risk of exposure to floods and riverbank erosion *before the 2021 monsoon onset* along the easternmost riverbank line of the Jamuna River.

Taken together, we propose we conducted our survey with a high-quality sample, exhibiting a high response rate, a very low attrition rate between survey waves 1 and 2 (see above), a random GIS-based sample of households within villages, and surveys conducted at nearly all inhabited locations with erosion risk along the left bank of the 250 km of the Jamuna River – offering strong external validity.

2.2.2. Main dependent and independent variables

We use two main dependent variables to capture migration aspirations (Carling & Collins, 2018). The first, current migration aspirations, is a binary measure with a value of 1 if a respondent expresses a preference for migrating over remaining in their current location *right now,* that is, at the time of the survey (0 otherwise). While this measure captures immediate migration aspirations, it can be highly volatile, influenced by the mood of the day. Therefore, we also use a second dependent variable that reflects respondents' migration aspirations in the *last month,* coded as a binary measure with a value of 1 if a respondent indicates having considered migration during the last month. These two core dependent variables are termed *"Aspirations (now),"* i.e., current aspirations, and *"Aspirations (past month),"* i.e., last month's aspirations, in our empirical analysis. In additional analyses, we use secondary dependent variables, namely the aspired *duration* (permanent vs. temporary) and the aspired *destination* (rural vs. urban) of migration (see Appendix Section A2.2 for details).

We use two main independent variables ('treatments'): households affected by either flood or riverbank erosion. We operationalize these independent variables as a binary indicator of whether a household reported having been *"Erosion affected"* or *"Flood affected*" in the previous monsoon season, i.e., four to six months prior to the survey. In additional analyses, we use secondary independent variables that classify erosion and flood affectedness into four levels of severity: *strong impact* (i.e., loss of house, total loss of land, permanent displacement), *some impact* (e.g., damage to the house, temporary displacement, partial loss of land), *other impacts* (e.g., partial loss of crops, reduced income, transport difficulties), and *no impact* (Appendix Table A.3 provides the complete list for these categories, including question-wording).

These independent variables rely on self-reported impacts of floods and riverbank erosion. We chose this operationalization strategy for three reasons: First, self-reported impacts provide a more nuanced measure compared to objective, satellite-based data, which can only indicate whether land was eroded (Freihardt & Frey, 2023). Second, objective data on flood extent and depth does not exist in our case, as cloud cover during the monsoon seasons prevents the collection of such objective data. Third, self-reported impacts are straightforward, factual questions that are relatively easy for respondents to answer.

2.2.3. Endogeneity concerns

Our data allow us to address various endogeneity concerns pertinent to researching migration aspirations. First and foremost, our sample selection strategy ensures we focus on a sample of households all at similar baseline risk of exposure, with natural processes affecting only some. This mirrors a quasi-experimental approach to social science research and allows us to cautiously interpret the direct comparison between affected and unaffected households as causal. Second, we can tackle three additional issues: A) actual migration – referring to potential respondents who left the area and are often absent in cross-sectional studies – can introduce bias into any straightforward comparison of migration aspirations between affected and unaffected households that remain in the area; B) self-reported impacts of floods and erosion might be biased in some way; C) affected and unaffected households might, despite our careful sampling strategy, still differ on pre-exposure characteristics (e.g., ex-ante risk perceptions) that could correlate with exposure to environmental events and migration aspirations.

Regarding A), it is crucial to note that we already sampled households pre-monsoon and tracked and re-interviewed the household heads who migrated.[3] This allows us to address the endogeneity concern of sample self-selection directly and include households of this migrant subsample in our estimation. Regarding our independent variable, affectedness by riverbank erosion and floods, we could measure this identically to the non-migrant subsample.[4] However, regarding our dependent variable, migration aspirations, we could not use standard survey questions – inquiring what aspirations a respondent would have had, had the respondent stayed *in situ* is cognitively too demanding and, hence, an unreliable measure. Nevertheless, we can impute migration aspirations for those household heads who migrated, assuming that migration represents 'realized' aspirations (Knox et al., 2020). Specifically, we assume that any respondent who actually migrated (and for whom we cannot measure migration aspirations at the time of the follow-up survey) would have had migration aspirations at that time. Hence, aspirations are coded as 1 for respondents who left the area between the 2021 monsoon onset and January 2022. Furthermore, we assume migration aspirations regarding duration and destination as observed for this subsample. This strategy enables us to estimate the relationship between exposure and aspirations without bias from sampling. As a robustness check, we additionally report effects only for the subsample of non-migrating households, which gives us a conservative estimate for any treatment effect. Appendix Section A2.3.1 provides details.

Regarding B), we acknowledge that previous research has identified discrepancies between subjective perceptions of environmental events, like flooding (Guiteras et al., 2015) and erosion (Freihardt, 2024) in Bangladesh, and corresponding objective data. To address this, we code a last independent variable, a binary indicator for *objective loss of house from erosion.* To derive this indicator, we use the erosion-detection tool as published by Freihardt & Frey (2023) who analyze Sentinel-1 radar satellite data, comparing shorelines before and after the monsoon to identify eroded land.[5] We matched this satellite-derived erosion data to the respondents' household locations as recorded during the survey. The indicator *objective loss of house from erosion* equals one if the pre-monsoon household location was on eroded land. We correlate this objective indicator to self-reported impacts (which show a significant association; see Appendix Tables A.5 and A.6) and perform robustness tests on impact measures using this objective treatment variable to address endogeneity concern B) directly. Appendix Section A2.3.2 provides further details on the comparison of objective and subjective erosion impacts.

Regarding C), we employ a procedure akin to matching, where we balance affected and unaffected households on various pre-exposure characteristics (e.g., ex-ante risk) that could correlate with exposure to environmental events and migration aspirations to caution against remaining bias. In detail, our baseline models allow for direct comparisons of respondents who reported being affected by floods and riverbank erosion and those who reported being unaffected. Since we observe a representative sample of households at risk of flood and riverbank erosion along the Jamuna River *before the monsoon onset*, this baseline comparison plausibly assumes that individuals cannot self-select into safe and unsafe locations on average. This assumption forms the core of our extensively pre-registered study design. If this assumption holds, we can directly relate quasi-random occurrences of erosion and flooding to migration aspirations. To add robustness to these estimates, we make affected households comparable to unaffected ones based on socio-demographic, geographic, and attitudinal characteristics *pre-treatment*. Appendix Section A.2.3 provides details on this approach. We perform extensive balance tests that yield two key findings: First, and most importantly, it is reassuring that pre-treatment differences in non-geographic indicators of socio-demographic conditions, migration behavior, and aspirations are minor and largely non-significant. However, as expected, given the large number of comparisons, some relationships between covariates (e.g., past aspirations and place attachment) and later exposure are statistically significant. Additionally, as anticipated, household affectedness is unevenly distributed in space, with some sampling locations seeing more exposure. Also, by design, erosion was more likely to occur in sampling zones 1 (closer to the river). This geographic clustering raises concerns as attitudes may also cluster based on geographic factors (Quoß & Rudolph, 2022). Hence, we cannot rule out the possibility that a correlation exists between erosion/flood affectedness and pre-existing attitudes. To address this, we argue that considering selection into treatment based on observable covariates (known as the conditional independence assumption) improves the credibility of a causal interpretation of our estimates. Consequently, we match treatment and control group observations on pre-treatment measures of geographic, socio-demographic, and attitudinal variables at both the individual and household levels, including pre-treatment measures for our outcome of interest, namely migration aspirations. Appendix Section A2.3.3.2 provides details on the included variables[6] as well as our rationale. We apply entropy balancing (Hainmueller, 2012) to compute sets of weights that achieve balance in the distribution of the first (mean), second (variance) and third (skewness) moments of these covariates for i) the erosion treatment and control groups and ii) the flood treatment and control groups. These weights ensure that the control groups' mean, variance, and skewness on 16 socio-demographic, geographic, and attitudinal variables correspond to those of the treatment groups. Our approach goes beyond mere statistical control of covariates and corresponds to a matching of observations in the group affected and unaffected by erosion or flood. Implicitly, we thereby also restrict our inference to the region of the covariate space where treatment and control groups have common support, improving inference (Lechner & Strittmatter, 2019). As shown in Appendix Table A.8 (for erosion affectedness) and Appendix Table A.9 (for flood affectedness), the algorithm performs very well in reducing differences to approximately zero. Hence, we assume that treatment status is more plausibly assigned *as if random* for both floods and erosion. Subsequently, we use these weights in the respective impact regressions.

2.3. Estimation strategy

We employ linear probability models, drawing on Ordinary Least Squares with

[3] We successfully reinterviewed 96% of non-migrating respondents and 81% of migrating respondents, indicating low attrition with both types of respondents. Attrition was higher among migrants, as migrants were more likely to miss interviews due to job obligations (see Table A1 for details).

[4] Households were interviewed during the same time periods; hence they experienced a similar recall period for environmental stress.

[5] In short, Freihardt (2025) use ground-range detected (GRD) data from both Sentinel-1A and −1B from the dry seasons 2014/15 to 2019/20 (defined as November 1 to May 1, respectively). The GRD scenes have been pre-processed by the Google Earth Engine following the steps from the European Space Agency's Sentinel-1 toolbox. The pre-processed images were filtered before the analysis according to acquisition mode, resolution, incidence angle, look direction, and polarization to create a homogenous subset of data. Per pass, one scene was used. Accuracy was assessed by comparing the Sentinel-1-based classification to an independently conducted classification based on optical Sentinel-2 imagery, showing a satisfactory accuracy of over 87%.

[6] Briefly, these measures include district of residence, distance to river, gender, education, age, number of children, income type, amount of land owned, assets owned (PCA index), house quality (PCA index), livestock units owned, place attachment, past migration experience, pre-treatment migration aspirations, risk preferences. All these variables are measured pre-treatment, i.e, in June 2021 before the monsoon onset, to ensure they are not affected by flood/erosion impact. Additionally, we also balance on occurrence of the respective other event (flood or erosion).

$$Y_i = \beta + \gamma X_i[+\mathbf{Z}_i\delta] + \epsilon_i[/\omega_{xi}]$$

Y_i is our core dependent variable, measured in two forms: current migration aspirations and last month's migration aspirations (early 2022). Hence, we estimate one impact regression for each of these two core dependent variables, which is the self-reported impact from erosion or flooding during the 2021 monsoon season. As shown by the bracketed weighting of error terms ϵ_i with weights obtained from entropy balancing for either erosion or flood affectedness, ω_{xi}, we estimate models both without and with the respective entropy balancing weights. Additionally, as indicated by the bracketed vector $\mathbf{Z}$, we also estimate models with and without the inclusion of pre-treatment control variables (see Appendix Section A.2.3.4 for a discussion of the controls used). Summary statistics for all variables are presented in Appendix Table B.20. Standard errors are clustered at the village level, as the treatment is clustered at this level (Abadie et al., 2017). We use linear probability models, as they allow for a more direct interpretation of the coefficients – specifically, the coefficient of flood or erosion affectedness can be directly interpreted as a percentage point change (in- or decrease) in migration aspirations associated with the impact of flood or erosion. For robustness, we also report logistic regression models in the Appendix, which yield fundamentally identical results. For additional analyses, we use secondary dependent variables that are categorical, namely aspired duration and aspired destination. This requires modifying the above approach, and we use multinomial models to estimate the effects. Last, for additional analyses, we use independent variables of erosion and flood affectedness differentiated by treatment intensity. For these subgroups of treatment intensity, we calculate specific entropy balancing weights to match each treatment intensity group and the control group and separately estimate the corresponding weighted regression models (see a similar approach in Chen et al., 2022).

Overall, our research design reflects a cross-sectional approach, incorporating pre-treatment covariates for balancing and as controls. Although a difference-in-differences (DID) design might appear to be a viable alternative, we deemed it inappropriate as pre-monsoon and post-monsoon migration aspirations represent different concepts. Perceptions of future risk shape pre-monsoon aspirations, while post-monsoon aspirations reflect a risk that has already materialized. Consequently, a DID design could reveal weak coherence between pre- and post-monsoon aspirations due to distinct psychological processes influencing these aspirations at different points in time.

3. Results

Next, we turn to our results. As discussed in the introduction, we expect that the coefficient γ will be positive and substantively relevant for erosion impact, smaller or close to zero for flood impact, and relatively larger for more intense impact categories than lower ones. Additionally, we expect erosion impacts to be more strongly associated with aspirations for long-term migration and more urban destinations.

3.1. Flood and erosion affectedness and migration aspirations

We begin by examining the relationship between aspirations and two indicators of flood and erosion affectedness and present the results across six different models in Fig. 2 for last month's and current aspirations (numeric regression results are presented in Appendix B, Tables B.1a and B.1b). Model (1) regresses migration aspirations on affectedness by erosion and affectedness by floods. For a causal interpretation, we would have to assume that exposure to these environmental hazards occurs quasi-randomly. In models (2) and (3), we include entropy balancing weights constructed from reweighting the control group such that it resembles the erosion treatment group (model 2) or flood treatment group (model 3) concerning control variables that could correlate with exposure. For a causal interpretation, these estimates assume selection-on-observables (but note that our research design already selected only households all at risk of flood/erosion). Models (4) to (6) mirror specifications (1) to (3) but additionally add control variables that may correlate with exposure directly to the regression. Hence, model (4), relative to model (1), now also addresses endogeneity concerns from observed third factors (albeit under modeling assumptions). Models (5) and (6), relative to models (2) and (3), improve efficiency and tackle any remaining endogeneity previously not yet addressed by balancing (Hainmueller, 2012).

Fig. 1 (right panel) illustrates that erosion, but not flood-affectedness, is associated with a significant increase in last month's migration aspirations. Specifically, erosion affectedness raises last month's migration aspirations by 22 percentage points in model 1 (without controls or entropy balancing (EB) weights) and by 16 percentage points in model 5 (our preferred specification, which includes EB weights and controls). This effect is statistically significant at the 1% level. It is also notably high: with the control group mean of 13 percentage points (see statistics for model 1 in Table B.1a), erosion affectedness more than doubles migration aspirations (an increase of 120% in model 5). The results for current aspirations (Fig. 1, left panel) show a similar, though slightly reduced, effect. In our preferred specification (model 5), erosion exposure raises current migration aspirations by 12 percentage points, representing an increase of 110% compared to the control group mean (see Table B.1b).

In the Appendix, Tables B.2 and B.3 present the results for the covariates not shown in models 4–6 of Tables 1 and 2. Both last month's migration aspirations (Table B.2) and current aspirations (Table B.3) increase significantly for men compared to women. At the same time, they decrease significantly and substantively with older respondents (compared to the baseline group of 18 to 30-year-olds). These findings align with existing literature. Additionally, a higher number of children in the household is associated with an increase in last month's migration aspirations. One explanation could be that larger household sizes create greater income pressure, potentially driving migration aspirations if local work opportunities are limited. Compared to a baseline of illiterate respondents, we find a U-shaped relationship between education level and migration aspirations. While migration aspirations decrease among respondents who have some education (primary or secondary school completed), they increase for those with higher education. The reason behind this could be that moderately educated respondents have multiple options *in situ* to change their income source when facing environmental changes. In contrast, highly educated respondents are overqualified for the local job market and thus are more likely to seek work elsewhere. Additionally, both higher levels of place attachment and greater amount of land ownership reduce migration aspirations. This is not surprising, given that both variables can be seen as proxies for the ties that a respondent has to their current location. Finally, respondents who expressed migration aspirations during the baseline survey in June 2021 *(any current migration aspiration)* showed increased aspirations in the follow-up survey in January/February 2022.

For Figs. 1 and 2, we used the sample of individuals who lived in their villages until the month before the monsoon onset, i.e., we included respondents who have since migrated. For those individuals, we set values for the dependent variables to 1, assuming their migration reflects their current and last month's migration aspirations. In the robustness section (Section 4), we report on estimates derived from only the subsample of households that remained *in situ*. With this approach, we estimate lower-bound effects by excluding all households that moved out of their village as well as those who shifted their house (i.e., relocated) within the village.

3.2. Categories of extent of flood and erosion affectedness and migration aspirations

Table 1 reports results based on the extent of erosion and flood affectedness as independent variables. Strong self-reported erosion affectedness increases last month's migration aspirations by 17 to 25

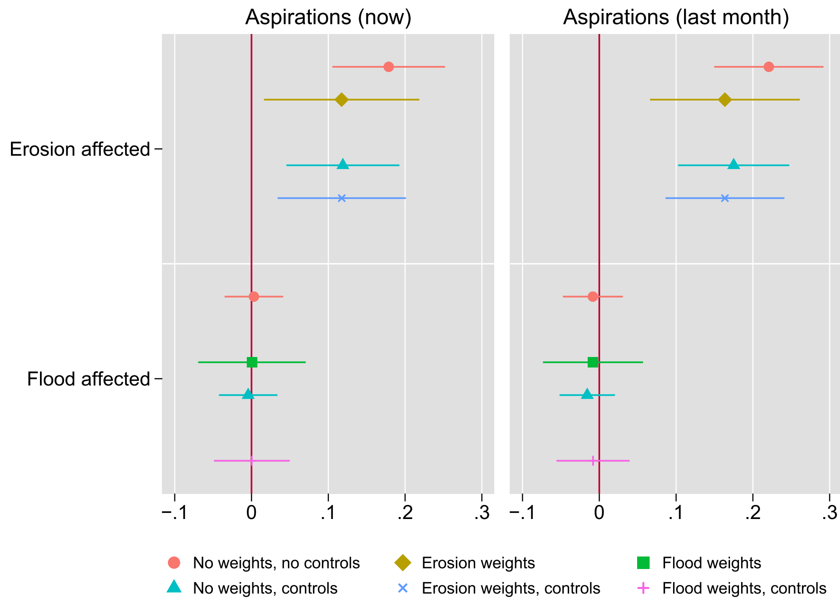

Fig. 2. ***Current and last month's migration aspirations and erosion/flood affectedness (OLS models).*** Note: Coefficient plot for six specifications of a linear regression model, regressing current migration aspirations (left panel) or last month's migration aspirations (right panel) on a binary indicator of erosion affectedness or flood affectedness (red circles), also including control variables (turquoise triangles), including entropy balancing weights for erosion affectedness (maroon diamonds) or flood affectedness (green squares), or weights with control variables (blue cross, pink plus). Whiskers show 95% confidence intervals from standard errors clustered by village. Sample: Households that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. Regression results displayed in Appendix Tables B1a/b and B2/3.

Table 1
Last month's migration aspirations and erosion/flood affectedness by impact category (OLS models).

	(1) Aspiration (past month)	(2) Aspiration (past month)	(3) Aspiration (past month)	(4) Aspiration (past month)	(5) Aspiration (past month)	(6) Aspiration (past month)	(7) Aspiration (past month)	(8) Aspiration (past month)
Erosion:	0.25***	0.21***	0.17**					
strong impact	(0.06)	(0.06)	(0.07)					
Erosion:	0.19***	0.17***		0.13***				
some impact	(0.04)	(0.04)		(0.04)				
Erosion:	0.15**	0.05			0.03			
other impact	(0.07)	(0.07)			(0.05)			
Erosion:	(ref)	(ref)	(ref)	(ref)	(ref)			
none reported	(.)	(.)	(.)	(.)	(.)			
Flood:	0.02	−0.05				−0.08**		
strong impact	(0.05)	(0.04)				(0.04)		
Flood:	0.01	0.00					0.00	
some impact	(0.02)	(0.02)					(0.03)	
Flood:	−0.08**	−0.06*						−0.05*
other impact	(0.03)	(0.03)						(0.03)
Flood:	(ref)	(ref)				(ref)	(ref)	(ref)
none reported	(.)	(.)				(.)	(.)	(.)
Flood affected			−0.02	0.00	−0.08			
			(0.05)	(0.02)	(0.07)			
Erosion affected						0.24***	0.17***	0.11**
						(0.06)	(0.04)	(0.04)
Controls	no	yes	yes	yes	yes	yes	yes	yes
N	1585	1271	997	1081	899	716	1087	758
Adj. R2	0.06	0.18	0.24	0.27	0.36	0.46	0.20	0.19
Mean erosion control group	0.13	0.13	0.24	0.19	0.20	0.41	0.25	0.18
SD erosion control group	0.34	0.34	0.42	0.39	0.40	0.49	0.43	0.38
Subgroup EB weights	no	no	erosion	erosion	erosion	flood	flood	flood

Note: Linear regression of dependent variable (as indicated in model header) on indicators of extent of flood and erosion affectedness. Entropy balancing (EB) weights and control variables used as indicated. Weights calculated for respective subgroups (i.e., only control group and group affected by respective erosion/flood impact category). Standard errors clustered by village in parentheses. Sample: Households that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. ** (***,*) indicates $p < 0.05$ (0.01,0.1).

Table 2
Current migration aspirations and erosion/flood affectedness by impact category (OLS models).

	(1) Aspiration (now)	(2) Aspiration (now)	(3) Aspiration (now)	(4) Aspiration (now)	(5) Aspiration (now)	(6) Aspiration (now)	(7) Aspiration (now)	(8) Aspiration (now)
Erosion:	0.24***	0.19***	0.15**					
strong impact	(0.06)	(0.06)	(0.07)					
Erosion:	0.12***	0.10***		0.06**				
some impact	(0.03)	(0.03)		(0.03)				
Erosion:	0.15*	0.00			0.01			
other impact	(0.07)	(0.07)			(0.06)			
Erosion:	(ref)	(ref)	(ref)	(ref)	(ref)			
none reported	(.)	(.)	(.)	(.)	(.)			
Flood:	0.06	−0.01				−0.05		
strong impact	(0.06)	(0.05)				(0.05)		
Flood:	0.01	0.01					0.00	
some impact	(0.02)	(0.02)					(0.03)	
Flood:	−0.05**	−0.03						−0.03
other impact	(0.02)	(0.02)						(0.02)
Flood:	(ref)	(ref)				(ref)	(ref)	(ref)
none reported	(.)	(.)				(.)	(.)	(.)
Flood affected			−0.01	−0.01	−0.09			
			(0.05)	(0.03)	(0.07)			
Erosion affected						0.15	0.10***	0.10**
						(0.09)	(0.03)	(0.04)
Controls	no	yes	yes	yes	yes	yes	yes	yes
N	1584	1270	997	1081	898	715	1086	757
Adj. R2	0.05	0.22	0.31	0.31	0.31	0.43	0.27	0.22
Mean erosion control group	0.11	0.11	0.23	0.18	0.24	0.38	0.20	0.14
SD erosion control group	0.32	0.32	0.42	0.38	0.42	0.49	0.40	0.35
Subgroup EB weights	no	no	erosion	erosion	erosion	flood	flood	flood

Note: Linear regression of dependent variable (as indicated in model header) on indicators of extent of flood and erosion affectedness. Entropy balancing (EB) weights and control variables used as indicated. Weights calculated for respective subgroups (i.e., only control group and group affected by respective erosion/flood impact category). Standard errors clustered by village in parentheses. Sample: Households that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. ** (***,*) indicates $p < 0.05$ (0.01,0.1).

percentage points, depending on the model specification, similar to the interpretation outlined above. Some erosion impacts also increase last month's migration aspirations, though to a lesser extent, with increases of 13 to 19 percentage points. Other types of erosion impact lead to substantively smaller effects – around three percentage points in model 5, our preferred specification – though these are not statistically significant at conventional levels. In contrast, strong and some flood impacts are not correlated with increased migration aspirations. Interestingly, in various models, strong and other flood impacts reduce last month's migration aspirations (by 8 and 5 percentage points, respectively, in models 6 and 8, our preferred specifications).[7] Regarding current aspirations (see Table 2), the results are substantively very similar to those for erosion impact categories, while the effects of flood impact categories are substantively closer to zero and are statistically insignificant. Specifically, for erosion impact, with decreasing impact extent, the relation with current migration aspirations becomes weaker: depending on modelling strategy, from 15 to 24 percentage points with strong impact to 6 to 12 percentage points for some impact, while other impact is substantively not discernable from baseline respondents, who did not report any affectedness-in our preferred specification (model 5) or when controls are included (model 2). In contrast, flood impacts show substantively smaller and statistically insignificant effects (models 6, 7, and 8). Overall, we find that higher self-reported erosion impacts are significantly associated with higher migration aspirations, whereas strong flood impacts do not show such a relationship.

3.3. *Flood and erosion affectedness and migration aspiration: Duration and destination*

Finally, Tables 3 and 4 provide additional insights by presenting results from multinominal regression models on the desired migration destination and intended duration, respectively.

Table 3 shows that being affected by environmental changes consistently increases the logit coefficients for aspirations to move to a rural destination. In contrast, the coefficient for an urban destination only reaches significance in model 1 (relative to no aspiration). Flood affectedness is not significantly associated with differences in the preferred migration destination. As reported in Table 4, regarding the aspired migration duration, erosion affectedness increases the logit coefficients for both temporary and permanent migration aspirations (compared to no aspirations). In contrast, flood affectedness does not significantly relate to aspired migration duration.

4. Robustness tests

The robustness section (see Appendix B for details) provides additional evidence on five key aspects, adding credibility to our proposed link between erosion affectedness and migration aspirations as well as the lack of a link between flood affectedness and migration aspirations, as discussed above.

First, we present logit models for all estimates examining the relationship between flood or erosion affectedness and last month's or current migration aspiration, as logit models are more appropriate for binary outcomes under certain conditions (Horrace & Oaxaca, 2006). As shown in Tables B.4–B.7, results are both substantively and statistically comparable with this statistical approach, confirming that our modeling choice does not affect our conclusions.

[7] These counterintuitive findings might also indicate that different impact categories are related to other potential confounders.

Table 3
Destination of migration aspirations among those reporting these aspirations (multinomial logit models).

	(1) Aspiration (destination)	(2) Aspiration (destination)	(3) Aspiration (destination)	(4) Aspiration (destination)	(5) Aspiration (destination)	(6) Aspiration (destination)
Stay						
Erosion affected	(ref)	(ref)		(ref)	(ref)	
	(.)	(.)		(.)	(.)	
Flood affected	(ref)		(ref)	(ref)		(ref)
	(.)		(.)	(.)		(.)
Rural						
Erosion affected	1.21***	0.95***		1.05***	1.12***	
	(0.17)	(0.24)		(0.20)	(0.21)	
Flood affected	0.00		0.08	−0.04		0.09
	(0.14)		(0.17)	(0.14)		(0.15)
Urban						
Erosion affected	0.86***	0.15		0.45	0.35	
	(0.29)	(0.38)		(0.36)	(0.40)	
Flood affected	−0.07		−0.25	0.06		−0.06
	(0.21)		(0.44)	(0.29)		(0.35)
Controls	no	no	no	yes	yes	yes
N	1566	1256	1256	1256	1256	1256
Pseudo R2	0.04	0.02	0.03	0.18	0.22	0.23
Mean erosion control group	0.20	0.30	0.36	0.20	0.30	0.36
SD erosion control group	0.49	0.60	0.61	0.49	0.60	0.61
Weights	no	erosion	flood	no	erosion	flood

Note: Multinominal regression of dependent variable (as indicated in model header, with three categories) on indicators of flood and erosion affectedness. Entropy balancing (EB) weights for affectedness by erosion or floods as well as control variables used as indicated. Models 2 and 3 and 5 and 6 also control for the respective other event that is not of primary interest for this regression (effect display omitted). Standard errors clustered by village in parentheses. Sample: Households that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. ** (***,*) indicates $p < 0.05$ (0.01,0.1).

Second, as outlined in the research design section, our sample includes both migrants and non-migrants, imputing the aspirations of migrants (set to 1) based on their realized outcomes. To provide a more conservative estimate[8] of the impact of affectedness on aspirations, we also estimate all models excluding households that have migrated, as this would be the standard approach of cross-sectional research, which typically does not observe households that migrated permanently, temporarily, or even those that shifted their house within the village.[9] The corresponding results are presented in Fig. B.1 and Tables B.8–B.13. The overall pattern shows that the erosion effects are attenuated in this biased sample, as expected since we excluded those households where aspirations migration aspirations were allegedly strongest – those whose aspirations have already materialized into actual moves. This attenuation is most pronounced for current migration aspirations (see Table B.8), particularly when respondents were asked whether they would prefer to leave the village immediately. In this case, we obtain no statistically significant effect for erosion affectedness, with coefficients close to zero (2 to 4 percentage points) and a marginally significant effect (at the 10%-level) only in the simple linear probability model. For floods, the coefficients are of a similar magnitude and consistently insignificant. Notably, as reported in Table B.9, this attenuation is only moderate for last month's migration aspirations. With this measure of our dependent variable, erosion is consistently related to increased migration aspirations. These are substantively relevant at 9 to 12 percentage points (about a doubling of the control group mean of 10–12%) and statistically significant at least at the 5%-level. For floods, as in our main estimation models, the relationship with last month's migration aspirations is positive but substantively much smaller in magnitude (estimated to be 1 to 4 percentage points and statistically insignificant). This pattern also holds across subgroups defined by the extent of erosion or flood affectedness. Generally, stronger erosion or flood affectedness is associated with stronger current aspirations. However, these relationships do not reach conventional levels of statistical significance (see Table B.10). Concerning last month's aspirations, the extent of erosion affectedness is linked to an increase in aspirations of about 15 to 17 percentage points for strong impact and around 10 to 11 percentage points for some impact, with significance at the 5% level. For floods, strong and some impact are associated with increases in last month's aspirations of about 4 to 6 percentage points when entropy balancing weights are included, where the effect for some impact is statistically significant at the 5%-level (see Table B.11). Our general findings also hold for destination and duration. As shown in Table B.12, erosion affectedness is statistically significantly associated with temporary *and* permanent migration aspirations, with a stronger link to temporary aspirations. Floods are weakly associated with temporary migration aspirations. However, this effect is not statistically significant across all models. As indicated in Table B.13, erosion affectedness is linked to increased aspirations of rural migration but not urban migration, and this relationship is statistically significant across specifications. For flood affectedness, no consistent pattern emerges.

Third, we seek to preclude potential biases from self-reporting the

[8] This interpretation as a conservative estimate assumes that the non-migrant sample excludes all respondents with realized, or in our view, the strongest developed aspirations. Appendix Table A.4 shows that, on average, these respondents exhibit lower place attachment, higher pre-treatment migration experience and aspirations, as well as fewer livestock units. These factors are generally associated with a greater likelihood of migration aspirations. Additionally, the migrant sample tends to be slightly more educated, younger, and more likely to be male.

[9] Note that for models using entropy balancing weights, the weights are adjusted to match the appropriate subsample, ensuring that no bias is introduced, as migrants and non-migrants differ on socio-demographics and additional characteristics (see Appendix Table A.4).

Table 4
Duration of migration aspirations among those reporting these aspirations (multinomial logit models).

	(1) Aspirations (duration)	(2) Aspirations (duration)	(3) Aspirations (duration)	(4) Aspirations (duration)	(5) Aspirations (duration)	(6) Aspirations (duration)
Stay						
Erosion affected	(ref)	(ref)		(ref)	(ref)	
	(.)	(.)		(.)	(.)	
Flood affected	(ref)		(ref)	(ref)		(ref)
	(.)		(.)	(.)		(.)
Temporary						
Erosion affected	1.25***	0.87***		1.00***	1.12***	
	(0.26)	(0.30)		(0.34)	(0.34)	
Flood affected	0.00		0.05	−0.15		0.05
	(0.21)		(0.40)	(0.24)		(0.26)
Permanent						
Erosion affected	1.08***	0.72**		0.88***	0.90***	
	(0.19)	(0.31)		(0.25)	(0.30)	
Flood affected	−0.05		−0.01	−0.01		0.03
	(0.16)		(0.17)	(0.17)		(0.16)
Controls	no	no	no	yes	yes	yes
N	1566	1257	1257	1257	1257	1257
Pseudo R2	0.04	0.02	0.03	0.22	0.26	0.27
Mean erosion control group	0.28	0.38	0.48	0.28	0.38	0.48
SD erosion control group	0.66	0.74	0.80	0.66	0.74	0.80
Weights	no	erosion	flood	no	erosion	flood

Note: Multinominal regression of dependent variable (as indicated in model header, with three categories) on indicators of flood and erosion affectedness. Entropy balancing (EB) weights for affectedness by erosion or floods as well as control variables used as indicated. Models 2 and 3 and 5 and 6 also control for the respective other event that is not of primary interest for this regression (effect display omitted). Standard errors clustered by village in parentheses. Sample: Households that did and did not move within 6 months, i.e., recoding temporary and permanent migrants as having (realized) past/present aspirations. ** (***,*) indicates $p < 0.05$ (0.01,0.1).

impact of events. Hence, we estimate the effect of objectively verified erosion at a respondent's pre-treatment household location on migration aspirations. As reported in Appendix Tables B.14 and B.15, for respondents who have objectively lost their house (based on satellite data showing that their pre-monsoon household locations are within the riverbed post-monsoon), migration aspirations increase substantively and significantly by more than 20 percentage points, for both current and past migration aspirations. These effects are comparable to the category of strong self-reported erosion affectedness. We estimate these effects using entropy balancing weights for the objective erosion indicator while controlling for (other) self-reported impacts from erosion and flood (to avoid bias in the control group).[10] Based on these findings, we are confident that our reported coefficients in Figs. 1 and 2 and Tables 1 and 2, which rely on self-reported impacts only, are valid.

Fourth, since our treatment is clustered at the village level, there might be a concern that it is not individual but rather village-level affectedness driving the results. However, Tables B.16 and B.17 show that this is not the case. There, we include the extent of affectedness at the village level (the percentage of households reporting flood/erosion affectedness) as an additional explanatory variable. While this village-level variable has a substantively relevant and statistically significant effect on migration aspirations, individual household aspirations remain strongly influenced by household-level affectedness. This suggests an important venue for future research: disentangling the potential effects of household-level versus village-level affectedness, where the former may reflect realized impacts, while the latter represents the potential risk of affectedness from future environmental change.

Fifth, we re-estimate our main models by recoding aspirations to zero for all respondents who indicated a desire to change location but highlighted in the location preference question that they would prefer to relocate within their own village. This adjustment helps reduce potential measurement error in our dependent variable, particularly if households expressing aspirations for within-village mobility had mistakenly reported aspirations for out-of-village migration (possibly due to a misunderstood question, for example). As shown in Tables B.18 and B.19, this recoding does not substantively alter our results.

5 Discussion and conclusion

Our study investigates whether and how environmental changes, specifically slow-onset riverbank erosion and sudden-onset flood events, affect migration aspirations. We argue that the migration aspirations of affected households are significantly shaped by the type of environmental event experienced, particularly the nature of the impact, whether reversible or irreversible. We find that slow-onset events, such as riverbank erosion, substantially increase both last month's and current migration aspirations, with increases of 16 to 22 percentage points for last month's aspirations and 12 to 18 percentage points for current aspirations. These increases roughly double the prevalence of migration aspirations compared to the control group with no such experiences. Effects are substantively similar for households experiencing both strong and some impacts of erosion, as compared to those with other impacts, i.e., lighter affectedness. In contrast, sudden-onset events like floods have little to no effect on migration aspirations *on average.* This suggests that the reversibility of damage – our key distinction between these types of events – may explain the differences in responses, at least for aspirations measured several months (4 to 6 months) after the event occurred. Taken together, our findings reveal that most individuals affected by

[10] Hence, we generate a categorical variable of erosion impact with the following values: 1-house lost from erosion (objective), 2-Else strong erosion impact (self-reported), 3-Else medium erosion impact (self-reported), 4-Else some erosion impact (self-reported), 5-Else no erosion impact (self-reported).

erosion or flooding do not exhibit increased migration aspirations about half a year after these events, yet aspirations to migrate rise significantly in response to more permanent environmental changes, such as riverbank erosion. Moreover, and against our expectations, these increased migration aspirations are primarily directed towards nearby rural areas rather than urban centers, which challenges existing literature that typically suggests a preference for urban destinations. Finally, none of our respondents indicated an aspiration to migrate internationally, reinforcing the growing body of research that shows environmental migration is predominantly internal (Clement et al., 2021; Kumari Rigaud et al., 2018). This nuanced finding adds to the literature on migration barriers, suggesting that, despite the availability of (domestic) job opportunities in urban areas (such as Dhaka, Chittagong, or Tangail in our case), affected populations may prefer to remain in their local areas, possibly due to strong place attachment. This insight has significant policy implications, highlighting the need for enhanced financial and technical support for local adaptation to long-term climate impacts, which could help reduce the need for long-distance migration.

Our finding that migration aspirations do not increase following flood exposure is not surprising, especially in riverine environments like Bangladesh, where small-scale flooding plays a crucial role in sustaining the agricultural productivity. The sediment deposited by floodwaters helps fertilize the fields, making flooding beneficial rather than purely destructive. Given the importance of water for growing rice – the primary staple food and the most significant crop in Bangladesh – natural flooding serves as a substitute for artificial irrigation, which is both time-consuming and costly to develop. This suggests that small floods are unlikely to have a statistically significant effect on migration aspirations, as they replenish the soil and nutrients in floodplains, making them highly fertile for agriculture. Moreover, the broader benefits of flooding, even in extreme cases, may outweigh the short-term costs by improving overall soil quality and increasing crop yields in subsequent cycles, which could raise the opportunity cost of migration, at least in the medium term. Indeed, recent studies from Bangladesh report either a negative relationship (Call et al., 2017; Chen et al., 2017), a modest effect (Gray & Mueller, 2012), or no effect (Lu et al., 2016) of floods on migration.

While flood impact is not significantly associated with any preferred migration destination or duration, erosion impact significantly increases aspirations for both temporary and permanent migration. Temporary migration, a well-established adaptation strategy to economic stress, including environment-induced economic stress, is common among Bangladeshi households (Call et al., 2017). The tendency for erosion to drive permanent migration, predominantly to rural areas, aligns with the findings of Chen & Mueller (2018), who found that soil salinity in Bangladesh leads to permanent migration, with mobility largely limited to nearby locations.

Regarding the external validity of our findings, we have strong confidence that our respondents represent a high-quality sample of the riverbank population at risk of erosion in Bangladesh. However, the extent to which our findings apply beyond the Bangladeshi context warrants further research, and we hope that our study design can serve as a useful template for this. That being said, it is important to note that riverbank erosion and flooding are not unique to the Jamuna River and other major rivers in Bangladesh; they also occur along significant rivers globally, such as the Mekong, Yellow, Mississippi and Danube Rivers. As such, the insights from our study are relevant beyond the specific case of Bangladesh. Moreover, our findings may also shed light on broader environmental changes, such as sea-level rise, where communities are facing slowly progressing, but long-lasting and permanent environmental shifts. In these contexts, erosion and sea-level rise often coincide with sudden-onset flood or storm events. The fact that these populations appear to adapt through sustained, local moves is a surprise finding, and it would be valuable to study whether there are potential tipping points when migration aspirations shift towards more distant locations.

Regarding policy relevance, we identify two key areas for future research: First, it is important to explore the heterogeneity in how different populations perceive environmental changes as threats and how these perceptions translate into migration aspirations and actual migration behavior. Factors such as dependence on the environment for income, risk preferences, and perceptions of future affectedness by environmental changes are likely to be critical in understanding these variations. Second, future research should examine how many of those who aspire to migrate actually follow through with moving. While linking aspirations to actual migration is beyond the scope of this paper, we plan to address this issue in our future work. In our survey, we followed the three-step approach suggested by Carling and Schewel (2018) and asked respondents who expressed migration aspirations about the likelihood of moving within the next twelve months and whether they had made any concrete preparations. Of those who expressed a desire to leave their village, 55% consider it likely or very likely that they would actually move, and 20% had already made some preparations for the move, such as purchasing land in another location. This percentage decline from general aspirations to specific plans to concrete preparations aligns with findings from other studies (e.g. OECD, 2015). While there is a percentage decline at each stage, these aspirations do not reflect people's dreams under ideal conditions but will materialize into actual moves for a certain fraction. Consequently, aspirations can serve as a more meaningful indicator of policy needs than the actual, realized migration outcomes (as reported, e.g., for our study area by (Freihardt, 2025)), as the latter often fails to capture the complexities of decision-making and may conflate aspirations and capabilities. Studying migration aspirations and their connection to environmental changes is thus a valuable pursuit.

CRediT authorship contribution statement

Lukas Rudolph: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Funding acquisition, Formal analysis, Data curation. **Vally Koubi:** Writing – review & editing, Writing – original draft, Funding acquisition, Conceptualization. **Jan Freihardt:** Writing – review & editing, Writing – original draft, Investigation, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Vally Koubi reports financial support was provided by Swiss National Science Foundation. Lukas Rudolph reports article publishing charges was provided by Project DEAL. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.

org/10.1016/j.gloenvcha.2025.102966.

Data availability

Replication data and code are available at Harvard Dataverse at https://doi.org/10.7910/DVN/4LLTJI.

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