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Climate-induced cross-border migration and change in demographic structure

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Abstract

As climate change threatens livelihoods in Bangladesh, migration to neighboring countries in South Asia may accelerate. We use multiple types of data to predict how changes in the environment affect cross-border migration. Nationally representative migration data are combined with remote-sensing measures of flooding and rainfall *and* in situ measures of monsoon onset, temperature, radiation, and soil salinity to characterize environmental migration patterns. We further evaluate which groups are more susceptible to cross-border migration to examine how environmental factors shape the demographic composition of the country. We find migration to neighboring countries declines with short-term, adverse weather but increases with soil salinity. The soil salinity effect remains particularly persistent among poorer households. Investments targeting risks faced by the poor and non-poor remain crucial, as retention of the earnings skills, and experience of the latter enhances national resilience.

Keywords Cross-border migration · Climate change · Bangladesh

Introduction

Sea-level rise predictions currently place 49% of the Bangladesh population, who live in the low-elevation coastal zone (LECZ), at risk of displacement (Neumann et al., 2015). The relationship between migration and atypical flooding during the monsoon

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season has received sufficient attention in the literature, due to widespread accounts of temporary displacement and the nature of humanitarian assistance drawn to the country during these periodic episodes (Penning-Rowsell et al., 2013; Call et al., 2017). Despite the pecuniary damage to infrastructure, flooding of this nature rarely influences migration within Bangladesh (Gray and Mueller, 2012; Lu et al., 2016; Chen et al., 2017). If previous findings are indicative of future behavioral responses to sea-level rise, the economic and social insecurity of millions living in coastal Bangladesh is imminent in the wake of global climate change without additional external efforts to support and initiate relocation programs (Neumann et al., 2015).

There are a few explanations for why the existing literature may fail to observe migratory responses to flooding. First, previous studies focus on precipitation-based or self-reported measures of inundation (Gray and Mueller, 2012; Call et al., 2017) rather than remote-sensing metrics which account for topographical characteristics when defining exposure (Guiteras et al., 2015; Chen et al., 2017; Davis et al., 2018). More importantly, they also ignore how exposure to flooding can intensify risk of salinity intrusion (Dasgupta et al., 2016; Chen and Mueller, 2018). The main sources of salinity arise from tidal inundation in low-lying deltas, use of irrigated water from contaminated surface and groundwater resources during the dry season, and the upward movement of salt from groundwater reservoirs (Clark et al., 2015; Payo et al., 2017). The lack of rainfall during the dry season renders farmers more susceptible to crop losses, due to the inability to dilute salt from the soil, replenish irrigated salt water with freshwater from upstream, and the extended usage of irrigated water to sustain crops (Dasgupta et al., 2014; Clark et al., 2015). Migration may be a viable adaptive response to the realization of salinity, given its detriment to rice productivity (Alauddin and Sharma, 2013; Alauddin et al., 2014) and the paucity of available high-yield varieties tolerant to high-saline content (Alpuerto et al., 2009). Therefore, analyses which incorporate more accurate representations of inundation as well as the additional dimension of soil salinity may improve the ability to empirically detect changing rates of environmental migration, assuming agricultural productivity losses underlie migration patterns (Feng et al., 2010; Cai et al., 2016).

Private adaptation to repeated inundation may offer a second reason for observed patterns of climate migration. Floods improve the quality of the soil, and, consequently, yields (Banerjee, 2010). In result, farmers have learned to adjust the duration of agricultural cycles to accommodate the sporadic timing of the onset of the monsoon and the ensuing heavy rainfall. In addition, farmers near rivers and coastal areas, the sources of most flooding, have begun to modify their cultivation practices to account for changes in inundation through extended cycling of aquaculture (Khanom, 2016).[1]

The dearth of studies validating flood-induced displacement may also arise from the absence of data measuring a variety of migration patterns engaged by individuals to cope with related risks. While destinations of environmental migrants are often within close proximity to their origin (Fussell et al., 2014), moving to an adjacent country may appear relatively more desirable to a migrant than moving to a major city in Bangladesh (Carrico and Donato, 2019). Increasing population pressure in cities has worsened the

[1] While these adaptive measures are critical coping strategies against crop losses from flooding, the creation of fish ponds can lead to deterioration of river embankments, exacerbating future flood risk. In coastal areas, households often engage in shrimp cultivation and voluntarily introduce saline water to create brackish ponds. This endangers future crop production through the enhancement of salinity in the water and soil, often leading to discord and conflict within communities (Sovacool, 2018).

competition for jobs, housing, and services, as well as exacerbated inherent disamenities, such as congestion and pollution (Alam, 2003). Although likely peripheral to the decision to relocate, many of these once prime destinations face similar threats of flooding and submergence. Thus, the employment prospects and quality of life available in neighboring countries may attract climate migrants, particularly in locations where they possess social or familial connections.[2] The increasing importance of cross-border migration to vulnerable households in the Global South is rarely quantified at the micro-level in the literature, with the main exception being for Mexico-US migration (Feng et al., 2010; Nawrotzki et al., 2015).[3] This is primarily due to a lack of nationally representative time series data on individual international migration patterns that can be linked to equivalent time-varying information pertaining to the individuals' demographics and wealth, *and* levels of climate exposure at the origin prior to migration. Micro-level assessments of climate migration remain important to inform the spatial and demographic targeting of future adaptation interventions.

We therefore use multiple types of data to predict how future changes in the environment in Bangladesh will affect mobility patterns to the South Asian subcontinent (Bhutan, India, Nepal, Pakistan, and Sri Lanka). Nationally representative migration data from 2005 to 2011 are collected through the Bangladesh Bureau of Statistics vital registration records. We combine the migration data with remote sensing measures of sub-district flooding and rainfall *and* in situ measures of monsoon onset, temperature, radiation, and soil salinity. With the exception of salinization, all environmental variables are reflected as anomalies over 1-, 2-, and 3-year periods to characterize migration patterns under different durations of exposure. We further evaluate which demographic groups are more susceptible to moving to an adjacent country to reflect how environmental factors may alter the demographic composition of the country.

Our analysis aims to identify potential hot spots for climate migrants in a region prone to natural disasters, elevated sea levels, and political insecurity. Over 15 million Bangladeshis have already manifested in India seeking asylum or economic opportunities, allegedly placing social and economic stress on receiving areas (Alam, 2003; Tripathi, 2016). To dissuade migrants from entering the country, a barbed-wire fence was constructed by India along the heavily trafficked border (Tripathi, 2016). Pressured by political constituents in key receiving areas, the government of India recently issued a national registry as well as maintains detention camps to regulate "illegal" immigration (Dutta, 2018). As climate change threatens livelihoods in Bangladesh, increased political unrest in this region may prompt the international community to consider providing additional support to accommodate climate change migrants both within and across borders.

[2] We are broadly generalizing the migrant's destination decision, where the density of the social network at a particular destination proxies reductions in moving costs and risks of unemployment through job contacts (Carrington et al., 1996; Munshi, 2003). However, Nawrotzki et al. (2015) interestingly find that access to social networks suppresses the probability of environmental migration as they offer would-be-migrants and their corresponding households other forms of adaptation to climate change at the origin.

[3] A few macroeconomic studies have examined the effects of climate on bilateral migration flows (Beine and Parsons, 2015; Cattaneo and Peri, 2016). A novel global study calculates the economic effect of sea level rise accounting for changes in a variety of factors, including migration using population data (Desmet et al., 2018).

Conceptual framework and key hypotheses

Lacking formal capital markets and insurance mechanisms, households in agrarian economies spatially allocate members of the family to mitigate known income risks determined by the historical distribution of environmental parameters (Rosenzweig and Stark, 1989) or environmental shocks (Halliday, 2006; Dillon et al., 2011). Cox et al. (1998) exploit the intergenerational transfers model to characterize the informal contract made between a migrant and his/her household. The model applies to situations in which the migrant is a child of the household head, which corresponds with the norm in many developing countries (Hoddinott, 1992; Hoddinott, 1994; Mueller, Doss, and Quisumbing, 2018). In the first phase, parents support the expenses of migrants in their search for employment outside of the community. In exchange, the migrant provides transfers at a later stage in the parental life cycle when income prospects may be limited. Contracts are reinforced by the parental threat of revoking land and asset bequests, as well as the possibility of severing the migrant's ties to the origin community, which offers informal insurance against unemployment and other forms of social capital (Hoddinott, 1992; Hoddinott, 1994; Melkonyan and Grigorian, 2012; de Brauw et al., 2013). The model can be broadly generalized to reflect an arrangement between a young family member and the rest of the household (Stark and Lucas, 1988) and extended to consider other types of inter-household transfers, such as those received from children who migrated for marital reasons (Rosenzweig, 1993).

Reducing total household vulnerability to environmental risks arises in two forms due to shifts in distance and sectoral diversification. First, migrants remain employed, or extend the family through new marital arrangements, at a distant location, lowering the household's total exposure to income risk, given the relatively low correlation between environmental variables at the origin and destination (Rosenzweig and Stark, 1989). Second, non-agricultural sectors, such as construction and services, that attract migrant family members to foreign locations (or nearby cities) will be largely immune to the environmental risks faced by standard agricultural enterprises (Colmer, 2018).[4]

We evaluate the extent households employ migration as a risk management strategy in Bangladesh, where a suite of environmental stressors threatens the income portfolio of households. In our context, cross-border migration that stems from climate risk may be motivated by a few mechanisms. Farmers may respond to the damages incurred on their own farm by sponsoring family members to migrate abroad to access auxiliary income (Cox et al., 1998).[5] Additionally, farmers may reduce their demand for hired agricultural wage laborers—those who aid in land preparation or harvesting—causing an increase in the supply of migrant labor within vulnerable communities (Jayachandran, 2006). These

[4] Emerging evidence from Chinese manufacturing firms suggests there may be long-term risks from gradual increases in temperature through its effect on both labor and capital (Zhang et al., 2017). Previous macroeconomic studies link changes in economic growth with changes in climate (Hsiang, 2010; Dell et al., 2012; Burke et al., 2015).

[5] Numerous assessments have deemed the prolonged submergence of land attributable to the 1998 "flood of the century" particularly damaging to markets and welfare in Bangladesh (del Ninno et al., 2003; del Ninno and Lundberg, 2005; Mueller and Quisumbing, 2011). Recent work has directed attention to the deleterious impacts of soil salinity, given changes in the amplitude and frequency of sea- level extremes from storm events and tides, on rice productivity (Alauddin et al., 2013, 2014).

channels suggest losses to agricultural income (Feng et al., 2010; Cai et al., 2016) or assets (Bohra-Mishra et al., 2014) underlie the use of migration to manage income risk.

A final mechanism underlying migration may relate to the evolution of perceptions on flooding risk, inducing households to engage in forward-looking adaptive behavior (Dillon et al., 2011; Kleemans, 2015; Quiñones, 2018). This channel is more difficult to verify for our environmental variables of interest, since we lack adequate data to represent the historical distribution of soil salinity and inundation. We further are unable to distinguish households by how they formulate expectations on future income without having conducted behavioral experiments parallel to the vital registration survey process. However, an empirical specification supportive of a positive relationship between cross-border migration and flooding would remain consistent with such forward-looking adaptive behavior, particularly in the absence of complementary changes in own income and assets. With these underlying drivers of environmental migration in mind, we examine the validity of the following hypothesis: *Exposure to flooding positively affects cross-border migration in Bangladesh, through the combined effects of inundation and soil salinity on livelihoods.*

Our main hypothesis implicitly assumes that households are able to overcome strong deterrents to international migration, which is particularly challenging among certain sub-populations within developing countries. The impoverished are unlikely to obtain the liquidity to finance international migration (Halliday, 2006; Bryan et al., 2014; Angelucci, 2015; Kleemans, 2015; Hirvonen, 2016; Bazzi, 2017). Moreover, only individuals with sufficient human and social capital endowments will be capable of securing employment abroad due to requirements on worker ability to transfer skills across sectors, converse in multiple languages, and possess soft skills in a setting with quite distinct social and cultural norms.[6] We therefore amend our first hypothesis to consider heterogeneity in cross-border migration response: *Households endowed with human (greater portion of male household members, greater portion of working age household members), social (practice Hinduism), or physical capital (greater assets) are more inclined to take advantage of employment opportunities abroad to minimize climate-related income risk.*[7] Empirical support for this hypothesis offers a link between climate change, brain drain, and a potential reversion in economic development (Drabo and Mbaye, 2015).

Data

Socio-economic data Migration poses unique challenges to data collection, as mobility makes respondents difficult to locate, particularly for large-scale surveys. On the other hand, longitudinal surveys with high quality tracking tend to be much more limited in size and scope, both temporally and geographically. Our data represents a sort of

[6] There are numerous additional barriers to migration that we cannot explicitly address in this paper. These barriers include having insecure property rights (de Brauw and Mueller, 2012; de Janvry et al., 2015), having a strong attachment to place (Bell et al., 2018), or even the psychic costs associated with moving (Sjaastad, 1962; Chen et al., 2019).

[7] The selection of household characteristics is limited to what was available from the survey data used in the paper.

middle ground. The Bangladesh Bureau of Statistics' Sample Vital Registration System (SVRS) is conducted annually to update inter-censal population statistics at the district (*zila*) level. Sampling is stratified at the locality level, to achieve representation across rural, urban, and metropolitan areas. Approximately 200,000 households (1 million individuals) are surveyed each year. The data include basic demographic characteristics, construction materials for the main dwelling, and use of improved sources of utilities and latrines. Chen and Mueller (2018) provide more details regarding the data collection process, sampling frame, and variables included in the SVRS.

Migration information is reported only for individuals who have been away for at least 6 months. Chen and Mueller (2018) provide a detailed analysis of internal migration (5.2%) and broad international migration (0.8%) responses to climate factors. We concentrate on the migration of individuals across the border here, given the geopolitical interest of future Bangladesh-India relations. For the main specifications, we focus on two migration-dependent variables, the number of migrants in the household going to South Asia and the number of migrants in the household going to India. The first outcome assigns a value of zero to households without migrants, households with internal migrants, and households with migrants that move to a location outside of South Asia. The second outcome adds a value of zero to households with migrants that move to a location in the sub-continent other than India to the original migration outcome. In alternative specifications, we omit households with internal and long-distance international migrants from the sample and include internal migration as a distinct outcome to provide support for robustness of results and aid in the interpretation of underlying mechanisms.

Summary statistics are presented in Table 1. One benefit of large administrative datasets is that, from 2005 to 2011, we have a total of 1,288,982 observations at the household-year level.[8] The flow of international migrants from Bangladesh is modest. In our sample, approximately 4.1 out of every 10,000 households had at least one member emigrating to the South Asia region (India, Pakistan, Nepal, Sri Lanka, Bhutan) within the last year. India is the most common destination by an order of magnitude. Household headship in the Bangladeshi context is predominantly male and Muslim, and adult literacy rates remain quite low at just under 50%. Most households in our sample are quite poor, with less than 10% having access to tap water, just over half having access to electricity, and only 59% using modern latrines.

Remote-sensing data Data on inundation are constructed from NASA's Moderate Resolution Imaging Spectro-radiometer (MODIS) satellite. Images are aggregated into 8-day composites that provide the best possible observation during the period, and each pixel in an image captures an area of 500 m^2. Cloud cover impairs visibility in satellite images, especially during the monsoon season. However, Islam et al. (2010) verifies the quality of the MODIS-based measure used here in Bangladesh, through its high

[8] With a dataset of this size, it is not unusual to have outliers particularly with respect to the age and household size variables. The outliers can arise at various stages of the survey process, from the miscalculation of the respondent at the interview stage, from the documentation of the interview at the transcription stage, and from the transfer of the information from paper to electronic form at the data entry stage. Fortunately, these occurrences of high values for the head of household's age and household size are rather sparse. Only 0.03% of the households in our sample report having more than 20 members and 0.2% of the households report having a head older than 90 years old.

Table 1 Descriptive statistics

	Mean	Std. Dev.	Min.	Max.
A. Migration rate (per 1000 households)				
Sub-Continent[a]	0.4143			
India	0.3398			
Pakistan	0.0334			
Nepal	0.0287			
Sri Lanka	0.0078			
Bhutan	0.0054			
B. Household-level socio-economic characteristics (N = 1,288,982)				
Head is male	0.8889	0.3143	0	1
Head's age	45.486	13.739	0	99
Head is literate	0.4978	0.5000	0	1
Head is Muslim	0.8806	0.3242	0	1
Head is Hindu	0.1038	0.3050	0	1
#Hh Members	4.8393	2.1967	1	101
Primary water, tap	0.0819	0.2742	0	1
Primary water, well	0.9032	0.2957	0	1
Secondary water, tap	0.0898	0.2859	0	1
Secondary water, well	0.4778	0.4995	0	1
Owns water source	0.5317	0.4990	0	1
Kerosene for light	0.4554	0.4980	0	1
Electricity for light	0.5315	0.4990	0	1
Kerosene for fuel	0.0040	0.0631	0	1
Electricity for fuel	0.0060	0.0772	0	1
Gas for fuel	0.0904	0.2868	0	1
Has modern latrine	0.5931	0.4912	0	1
Coastal district	0.2974	0.4571	0	1
Border district	0.4459	0.4971	0	1
C. Sub-district level environmental conditions (N = 2633)				
Saline contaminated soil[b] (%)	6.3482	17.315	0	88
Proportion area inundated[c]	0.1880	0.2030	− 0.2257	0.9396
Avg. min. temp.[d] (°C)	21.3440	0.7269	19.436	23.040
Avg. max. temp.[d] (°C)	30.7672	0.7125	29.217	32.918
Bright sun[d] (h)	6.1184	0.4735	3.9250	7.4667
Total annual precipitatione (mm)	2364.8	679.53	1153.9	7231.4
Monsoon onset[f]	28.6293	24.519	0	201

Statistics in A and B calculated at the household level from the Bangladesh Bureau of Statistics' Sample Vital Registration System, 2005–2011

[a] Includes India, Pakistan, Nepal, Sri Lanka and Bhutan

[b] Soil Research Development Institute, Ministry of Agriculture, Govt. of Bangladesh

[c] Moderate Resolution Imaging Spectroradiometer, NASA

[d] Weather stations, Bangladesh Meteorological Department

[e] Tropical Rainfall Measuring Mission, NASA

[f] Number of days after1 May. Rainfall stations, Bangladesh Water Development Board

correlation with more reliable measures which can only be constructed over small geographic and temporal scales.

Following previous studies in Bangladesh (Guiteras et al., 2015; Chen et al., 2017; Chen and Mueller, 2018), inundation is represented by the Modified Normalized Difference Water Index (MNDWI) (Xu, 2006). The MNDWI delineates water and non-water features based on differences in surface reflectance, and provides greater accuracy than other available band-ratio indices (Ji et al., 2009; Ogilvie et al., 2015). A pixel with an MNDWI value greater than 0.1 is considered water. To translate pixel information to the sub-district (*upazila*) level, we use the maximum percentage of water pixels over all 8-day composites in the period. Sub-district level inundation is captured by the difference in the percentages of water pixels between the monsoon (July–Dec) and dry (Jan–Mar) seasons within a given year to distinguish water bodies from flooding.

Data on rainfall are drawn from NASA's Tropical Rainfall Measuring Mission (TRMM), which generates precipitation values of 0.25 x 0.25° resolution. Although correlations between TRMM and rain gauge data remain remarkably high, the reliance on daily measures extrapolated from TRMM can produce biased estimates for specific regions (dry vs. wet regions) during specific seasons (pre-monsoon vs. monsoon) (Tarek *et al.*, 2017). Following the recommendation of Islam and Uyeda (2007), we therefore focus on monthly precipitation values extracted from TRMM, aggregated up to annual measures, to reduce the measurement error that can arise from missing observations from specific rainfall gauges and the bias that may arise from using daily measures on our parameter estimates of interest.

In situ data The Bangladesh Meteorological Department's (BMD) has 34 weather stations around the country, roughly one station per district (Fig. 3). These stations collect hourly information on temperature and rainfall, and monthly information on bright sun exposure. We fill the data gaps from missing observations with values obtained from the closest station. From this data source, we create annual averages for minimum and maximum temperature and bright sun exposure.

The timing of the monsoon is a significant predictor of yields in rainfed agriculture (Rosenzweig and Binswanger, 1993). Daily TRMM data have been documented to overestimate pre-monsoon rainfall in dry areas and underestimate rainfall during the monsoon period in wet regions of Bangladesh (Islam and Uyeda, 2007). We therefore use a more comprehensive source of daily rainfall data (500+ weather stations) from the Bangladesh Water Development Board to generate an explanatory variable for monsoon onset. Following 1st May, we consider the day to be the onset of the monsoon if it follows three or more days which had rainfall amounts of at least 5 mm (Ahmed and Karmakar, 1993). The units of our explanatory variable are expressed as the number of days after 1st May.

Measures of soil salinity are based on field surveys conducted in 18 of the 64 districts of Bangladesh by the Soil Resource Development Institute, an agency of Bangladesh's Ministry of Agriculture (SRDI, 2012). Detailed topographical, aerial, and landform maps were used to draw traverse lines 3–4 km apart throughout the coastal region (excluding the protected Sundarbans area). Along the traverse lines, a total of 2500 soil samples were collected and tested for electrical conductivity and pH in 1988, 2000, and 2009. From these values, 2005 (2006–2011) salinity is classified by whether the electrical conductivity is greater than or equal to 2.0 dS/m in 2000 (2009).

Our measure of soil salinity exposure is then the percentage of land area in each sub-district with saline contamination. Of the 147 sub-districts in our sample, 32% have no discernible soil salinity in both surveys, 31% have a decrease in the percentage of saline-contaminated land between 2001 and 2009, and 37% have an increase. Sub-districts outside the coastal region are, by default, assigned a value of zero for soil salinity. Therefore, our estimates should be interpreted as the effect of salinity in the coastal region specifically and may not be applicable to cases of inland soil salinity (e.g., via irrigation, saline groundwater).

Methodology

Our primary outcome of interest is the number of cross-border migrants from each household. We focus on destinations closest to Bangladesh: India, Pakistan, Nepal, Sri Lanka, and Bhutan.[9] India alone accounts for a little over 80% of the migration to this region, so we also examine migration flows to this specific destination. The long and rocky history between these two countries, along with rising tensions between ethnic and religious groups in border areas (Schultz, 2018), also make this a particularly pressing policy concern. To estimate the effect of environmental factors on the flow of migrants, we utilize a negative binomial specification to account for the outcome being a count variable with over-dispersion. The regression equation can be expressed as follows:

$$M_{hjt} = \boldsymbol{\beta Z}_{hjt} + \boldsymbol{\delta X}_{hjt-1} + \theta_S S_{jt-1} + \theta_{S,1988} S_{j1988} + \tau_t + \mu_{hjt}, \tag{1}$$

where M represents the number of migrants to a specific destination from a household h in sub-district j at time t.

We include a suite of environmental variables in $\boldsymbol{X}$ that are known to affect rice yields in Southeast Asia. In particular, we use flooding, total annual precipitation, average annual minimum and maximum temperatures, average annual solar radiation, and the annual onset of monsoon rainfall, all lagged by 1 year. Rosenzweig and Binswanger (1993) first demonstrate the importance of monsoon onset and total precipitation on the profitability of farmers in India. They found that a delay in the monsoon and an increase in the cumulative rainfall per season dampens the profit of farmers in ten villages in India. Banerjee (2010) exemplifies the benefits of normal flooding on crop productivity by comparing rice yields across districts over years with and without flooding in Bangladesh. Welch et al. (2010) highlight how the minimum and maximum temperatures, as well as the solar radiation, a plant is exposed to at different growth stages render differential effects on rice yields. Specifically, increases in minimum temperature can damage rice yields owing to the biological processes that are affected during the vegetative and ripening phases (Welch et al., 2010), while similar increases in maximum temperature values can induce a positive agronomic response particularly when there are fewer

[9] Migration to these countries accounts for 38% of international moves, where the remaining share of migrants arrives in the Middle East.

cases of maximum values exceeding a threshold of 35 °C. They also show the importance of accounting for solar radiation when estimating agronomic relationships, as an increase in radiation harms plants during the vegetative phases and aids plants during the ripening phases.

With the exception of the monsoon onset date, we standardize the environmental variables with the sub-district or weather station-specific mean and standard deviation. Onset of the monsoon is normalized to be the deviation from the mode onset date for the sub-district over the previous 30 years. Our estimates, therefore, reflect responses to abnormal weather conditions rather than prior and/or long-standing adaptation strategies. This approach is in lieu of using level versions of the environmental variables in a regional fixed effects model. The relatively limited temporal and spatial coverage of our environmental variables, particularly salinity and radiation, suggest that our control variables are measured with error. The inclusion of fixed effects would exacerbate this measurement error and lead us to understate the importance of environmental factors in international migration.

In addition to the environmental variables in $\boldsymbol{X}$, we include a measure of soil salinity, S_{t-1}. Soil salinity is often caused from the saturation of sea water in groundwater and surface water sources along the coast. The effect of soil salinity on livelihoods can be more devastating to agricultural production in the long term than inundation itself, influencing individuals to migrate from their homes (Chen and Mueller, 2018). This is because soil salinity is a direct result of salt leaching into the soil from the sea water and entering the root of the crop through evapotranspiration (Clark et al., 2015). Moreover, farmers do not have access to saline-tolerant rice varieties to adapt to any long-term changes in soil quality generated from a rise in sea level (Alpuerto et al., 2009). In contrast, while riverine flooding has been shown to delay agricultural cycles, the inundation of fresh water benefits rice production as it enriches the nutrients of the soil (Banerjee, 2010) leading to more temporary migration episodes to evade the short-term damages to infrastructure (Call et al., 2017). Because our remote sensing measure of flooding cannot distinguish by the source of inundation, the inclusion of soil salinity is crucial as it arguably reflects a more direct livelihood consequence from a rise in sea level.

Data on salinity are sparser, due to the high cost of soil testing. As described above, soil salinity estimates from the year 2000 are linked to migration data for 2005, and findings from 2009 are linked to years 2006–2010. There is a high degree of variability in soil salinity over time, as it is determined not only by tidal flooding but complex processes involving rainfall, elevation, irrigation, and crop choice. Therefore, standardizing the salinity measure does not account for underlying heterogeneity in the risk of saline contamination. Instead, we control for historical soil salinity S_{1988}, motivated by the observation that the total salt affected area has expanded fairly steadily over time, with an increase of 26.7% between 1973 and 2009.

We further condition on $\boldsymbol{Z}$, which includes household demographic and wealth variables known to influence agricultural production: age, age-squared, literacy, and religion of the household head; the number of household members in eight age-sex categories (number of male/female household members 0–5, 6–

16, 17–54, and greater than 54 years old); indicators for whether the household is in the coastal zone[10] or the drought-prone areas of the Northwest[11]; indicators for whether the household has improved water and latrine facilities (primary/secondary water source comes from tap/well, has own water source, has modern or sanitary latrine); and sources of energy (has kerosene/electricity as a source of light/fuel, has gas as a source of fuel). Aggregate time-specific factors that influence agricultural production and prices are captured by a time fixed effect τ_t. Finally, standard errors are clustered at the sub-district level, the unit of measurement for environmental exposure, to allow for spatial correlation in unobserved factors influencing migration (Bertrand et al., 2004).

To explore additional dimensions of the international migration-environment nexus, we estimate two alternate specifications. First, we construct 2- and 3-year lags for temperature, radiation, and rainfall to look for persistent migration effects over time. This is done by first averaging the lagged values and then standardizing based on the long-run mean and standard deviation for the sub-district. Second, we estimate an expanded model that includes interactions between our environmental variables and group-level indicators (G) as follows:

$$M_{hjt} = \boldsymbol{\beta Z}_{hjt} + \left(\boldsymbol{\delta}+\boldsymbol{\delta^G}\right)\boldsymbol{X}_{hjt-1} + \left(\theta_S + \theta_S^G\right)S_{jt-1} + \left(\theta_{S,1988} + \theta_{S,1988}^G\right)S_{j1988} + G_{hjt} + \tau_t + \mu_{hjt}. \quad (2)$$

The coefficients on the un-interacted variables then indicate the baseline response, while the interaction effects then show how and if the response differs significantly across groups. In one set of specifications, groups are defined by geographic region—districts in the coastal zone at risk of saline intrusion, and districts along the Bangladesh-India border. In a second set of specifications, groups are defined according to the gender/age composition, wealth, and religion of the household. This allows us to test our second hypothesis and determine whether migration responses differ with household endowments. Specifically, we compare households grouped by religion and by whether their values for the following variables are above or below: the median number of female household members divided by the total number of household members (sex ratio); the median number of household members age 35 or older divided by the total number of household members (age ratio); and the top quintile for the asset index. For the latter, we use principal components analysis to construct an asset index based on the survey indicators for household water and energy sources[12] (Filmer and Pritchett, 2001).

[10] A value of 1 is assigned to the following districts: Satkhira, Jessore, Narail, Gopalganj, Khulna, Bagerhat, Pirojpur, Barguna, Jhalokati, Patuakhali, Barisal, Bhola, Shariatpur, Chandpur, Noakhalim, Feni, Lakshmipur, Chittagong, Cox's Bazar, and Madaripur. Note that, because salinity data is available only for these districts, the coastal indicator accounts for both regional differences in migration and the mass point at zero in our salinity measure.

[11] A value of 1 is assigned to the following districts: Bogra, Joypurhat, Naogaon, Pabna, Rajshahi, Dinajpur, Rangpur, Nilphamari, Sirajgong, Kurigram, Lalmonirhat, Nawabgong, and Natore.

[12] Specifically, the variables used to build the index are: whether the primary water source comes from a tap, whether the primary water source comes from a well, whether the secondary water source comes from a tap, whether the secondary water source comes from a well, whether the household has its own water source, and whether the household has a modern or sanitary latrine.

Results

We first focus on the migration effects of climate factors typically investigated in the literature. Table 2 presents our results from our main specification (1), with coefficients reported as incidence rate ratios.[13] Higher than usual sun exposure and precipitation have significant negative effects on migration to other South Asian countries. A 1 standard deviation deviation increase in radiation reduces the likelihood of migration by about 33%, and the effect for rainfall is even larger at roughly 50%. Maximum temperature also has a negative effect, though it is not significant at conventional levels (p value = 0.16). All three factors have been found to reduce rice yields in this region (Welch et al., 2010 and Auffhammer et al., 2012).

Looking over longer time frames (Table 2, B and C) reveals similar effects, and also provides empirical support that certain types of shocks can have enduring consequences on cross-border migration. For example, we observe a 33% decline in cross-border migration, when framing a radiation shock according to the value realized in the previous year, while we observe an additional 10% decline in cross-border migration when averaging radiation shocks over the previous 3 years. A larger effect on migration rates is also visible when comparing across specifications of precipitation: a 1 standard deviation increase in the 3-year averaged precipitation anomaly leads to an additional 3% decrease in migration compared with the 1-year lagged precipitation anomaly.[14] Effects for migration to India are again similar in sign and magnitude. We also present specifications controlling for 1-, 2-, and 3-year lags separately, to see if effects have a more specific temporal pattern. In Appendix 2, we see some suggestive evidence that the effect of weather shocks endures yet diminishes over time, particularly for temperature, but our point estimates are less precise.

Flooding and cross-border migration

To test the validity of our first hypothesis, we examine whether the estimated parameters on the inundation and soil salinity variables are each positive. Flooding is found to have a significant negative effect on migration. A 1 standard deviation increase in the area inundated reduces migration by 14%. Countervailing effects of inundation on production may explain the negative relationship between international migration and inundation. Inundation, particularly in extreme cases such as typhoons, has been documented to cause large crop losses (Redfern et al., 2012). However, riverine flooding has also been found to increase yields in subsequent years due to its positive effect on soil nutrients (Banerjee, 2010). Our flooding coefficient could therefore reflect the lack of funds available to the household to finance an international move (Stecklov et al., 2005; Angelucci, 2015) or the positive flooding externalities to production which may draw household members back to work in the fields (Banerjee, 2010).

In contrast with findings on inundation, higher soil salinity, which has a clear negative effect on rice yields (Hussain et al., 2018), renders a significant and very large positive effect on migration. A 1 standard deviation increase in salinity increases migration by a

[13] An incidence rate ratio less than one indicates a lower risk of the incident occurring, while a ratio greater than one indicates a higher risk.

[14] Due to lack of data, we are unable to trace out a similar effect for salinity.

Table 2 Environmental migration patterns by destination and time frame

	A. 1-year lag		B. Average of 1- and 2-year lags		C. Average of 1-, 2-, and 3-year lags	
	Sub-continent	India	Sub-continent	India	Sub-continent	India
Avg. min. temp.	0.804 (0.174)	0.760 (0.121)	0.771 (0.120)	0.730* (0.0856)	0.765 (0.130)	0.725* (0.0958)
Avg. max. temp.	0.883 (0.338)	0.812 (0.148)	0.838 (0.266)	0.776 (0.158)	0.882 (0.445)	0.820 (0.278)
Bright sun	0.666*** (6.80e−06)	0.678*** (0.000130)	0.590*** (1.16e−06)	0.615*** (3.48e−05)	0.528*** (1.85e−07)	0.537*** (2.16e−06)
Total precipitation	0.498*** (1.21e−06)	0.561*** (0.000120)	0.452*** (6.62e−07)	0.510*** (5.53e−05)	0.466*** (1.15e−06)	0.520*** (6.70e−05)
Flooded area	0.857* (0.0569)	0.811** (0.0152)	0.743** (0.0227)	0.699** (0.0147)	0.796*** (0.00383)	0.758*** (0.00128)
Saline area[a]	1.039*** (0.000481)	1.039*** (0.000448)	1.037*** (0.000667)	1.037*** (0.000622)	1.040*** (0.000345)	1.040*** (0.000330)

Notes: Socio-economic data drawn from Sample Vital Registration System, 2005–2011, Bangladesh Bureau of Statistics. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Saline soil represents the percentage of total upazila land area affected by saline contamination. Includes controls for historical soil salinity, rainfall, min/max temperature, sun, monsoon onset, demographic and wealth controls, region, and year-fixed effects. Negative binomial regression with effects reported as incidence rate ratios. Standard errors clustered at sub-district level. p values in parentheses

*10%, **5%, ***1%—levels of significance (N = 1,288,982)

[a] Only 1-year lag available

factor of 18.[15] The effects are very similar when looking at migration to India and estimates become more precise, particularly for flooding. This suggests that motives to migrate to other countries in the region are more heterogeneous, while migration to India is more strongly linked to flooding risk factors. For robustness, we also present results using alternate measures of migration in Appendix 3. When looking at an indicator for whether the household had any cross-border migrants, as well as the number of male and female international migrants separately, our results are identical with regard to sign, significance, and relative size and remarkably similar in magnitude.[16]

While the focus of this paper is the impact of climate on cross-border migration (see Chen and Mueller (2018) for an analysis of internal migration and broader international migration), we also estimate a multinomial logit that treats migration destinations as competing alternatives for resilience. In Appendix 4, we see that the estimates for migration to India are nearly identical in sign, significance, and magnitude to those in Appendix 3, which utilize an indicator for migration to India. Estimates for migration to other South Asian countries are also similar (note that, in the multinomial logit, the category "other S.Asia" excludes India whereas, in Appendix 3, migration to India is included in the indicator for migration to the Asian sub-continent). We also find significant effects of climate on "mixed" strategies that involve simultaneously sending migrants to several destinations (e.g., internal and India/South Asia). This reveals a new layer of complexity in the climate-migration relationship and is an important area for future research.

The large, positive migration effect from an increase in soil salinity lends credence to the first hypothesis. Flooding is found to have the smallest negative effect on migration, consistent with the finding that flooding can be beneficial in subsequent years. Retaining family members to help achieve the yield improvements brought by the nutrient-fortified soil appears to outweigh the expected benefits of sending them migrate (Banerjee, 2010). To examine the extent the combined migration effects of inundation and soil salinity are positive, in the next sub-section, we will predict the number of expected migrants from areas exposed to flooding and soil salinity among residents of the coastal zone.

A significant drawback of using a large administrative dataset is the lack of detailed survey questions that would allow us to explore more carefully the motives for and impediments to migration. Therefore, we can only speculate as to what mechanisms may drive the distinct migration patterns driven by inundation and soil salinity in light of the existing literature. Income losses from short-term flooding may tend to create liquidity constraints that impede migration or encourage the choice of internal destinations over cross-border migration (Kleemans, 2015). Households may also increase use of family labor on the farm to offset adverse flooding conditions or in local off-farm employment rather than engage in costly and risky migration (Bryan et al., 2014). In contrast, salinity in the soil is slow to dissipate. Its large positive effect on migration may suggest that households are cognizant of which factors will have persistent adverse effects on local livelihoods and are responding accordingly (Dillon et al., 2011; Quiñones, 2018).

[15] The figure is calculated by multiplying the incidence rate ratio (1.039) by the standard deviation of salinity reported in Table 1 (17.255).

[16] Additionally, we find a significant negative effect of minimum temperature, suggesting that colder weather may "tip" households into international migration, particularly for males.

Regional differences in observed migration patterns

Adaptation strategies may vary geographically due to variations in environmental risk as well as relative ease of travel. Saline contamination is a prominent issue in the coastal zone. Yet, mobility costs may decrease the desirability of migrating abroad to avert environmental risks. Thus, use of migration as an adaptation strategy may be more desirable among inhabitants in districts along the Bangladesh-India border, where transportation costs are likely lower.

We first focus on differences in exposure to risk restricting the analysis to the coastal zone which are estimated using regression equation (2) (bottom panel of specification A, Table 3).[17] Flooding leads to much smaller negative migration effects in the coastal zone that are not statistically different from zero. The muted effect of inundation on migration out of coastal districts may be driven by either lower barriers to move to the destination or the heightened exposure to flooding associated with storm surges experienced on the coast.

We compare the migration effects observed among households residing in the coastal zone with those obtained when restricting the focus to districts bordering India to assess the relative importance of moving costs on cross-border migration decisions. Here, we find that cross-border migration is no more responsive to environmental shocks, despite lower migration/transaction costs. The effect of flooding also appears to be more muted, and the estimated coefficients are no longer statistically significant at conventional levels. Grouping districts by proximity to the Indian border seems to lump together heterogeneous responses to flooding, resulting in imprecise estimates. Taken together, the findings suggest that use of migration as adaptation, particularly cross-border migration, will depend less on travel costs than on the specific type of shock experienced. This is clearly evidenced by the significance of soil salinity, distinct from inundation. Unfortunately, without additional data on flooding incidents, we cannot provide more specific insight on whether, for example, migration is more responsive to coastal versus inland flooding or to widespread versus localized flooding events.

We predict the change in the number of out-migrants to India from each district for a 1 standard deviation increase in soil salinity (Fig. 1) and inundation (Fig. 2), respectively, to assert flooding risk increases cross-border migration per our first hypothesis. The figures are based on estimates produced from the model presented in panel A of Table 3 and are based on 2011 out-migration rates, the most current year for which we have vital statistics. The negative binomial specification allows us to account for over-dispersion of migrant counts in estimating how environmental factors affect migration. That is, we estimate the effect of flooding and salinity on the incidence of cross-border migration, but we cannot predict when specific cases will switch from zero to positive out-migration. Therefore, our maps reflect, in large part, the high prevalence of districts with no international migrants in 2011.

Interestingly, we see that cross-border migration is generally more prevalent in coastal districts, particularly those on the western side. Figure 1 shows that an increase in salinity leads to much larger population flows from Bangladesh to India. For the districts with the largest response, Bagerhat and Satkhira, migrants appear to be even bypassing the large

[17] All districts outside the coastal zone are assigned a value of zero for salinity, based on the design of the soil sampling survey. Therefore, the effect of salinity can be estimated only for the coastal region.

Table 3 Environmental migration patterns by region

	A. Saline risk		B. Proximity to border	
	Sub-continent	India	Sub-continent	India
Avg. min. temp.	0.959 (0.835)	0.861 (0.530)	0.774 (0.148)	0.751 (0.146)
Avg. max. temp.	0.872 (0.500)	0.692 (0.102)	0.874 (0.374)	0.802 (0.161)
Bright sun	0.524*** (0.00272)	0.564** (0.0207)	0.616*** (7.56e-05)	0.607*** (3.64e-05)
Total precipitation	0.514*** (0.00160)	0.511*** (0.00389)	0.537*** (0.000887)	0.621*** (0.00956)
Flooded area	0.779* (0.0754)	0.698** (0.0220)	0.936 0.858 (0.546)	(0.191)
Saline area[a]	n/a	n/a	1.039*** (0.000843)	1.040*** (0.000429)
	Relative effects			
	Coastal zone[b]		Bordering India[b]	
Avg. min. temp.	0.727 (0.270)	0.812 (0.493)	0.995 (0.988)	1.062 (0.852)
Avg. max. temp.	1.033 (0.883)	1.302 (0.268)	0.800 (0.253)	0.805 (0.303)
Bright sun	1.382 (0.167)	1.246 (0.393)	1.201 (0.357)	1.265 (0.224)
Total precipitation	1.047 (0.867)	1.209 (0.520)	0.707 (0.233)	0.649 (0.160)
Flooded area	1.199 (0.301)	1.273 (0.200)	0.838 (0.279)	0.907 (0.566)
Saline area[a]	1.039*** (0.000469)	1.039*** (0.000423)	1.008 (0.0201)	1.001 (0.0202)

Notes: Socio-economic data drawn from Sample Vital Registration System, 2005–2011, Bangladesh Bureau of Statistics. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Saline soil represents the percentage of total upazila land area affected by saline contamination. Includes controls for historical soil salinity, rainfall, min/max temperature, sun, monsoon onset, demographic and wealth controls, region, and year-fixed effects. Negative binomial regression with effects reported as incidence rate ratios. Standard errors clustered at sub-district level. p values in parentheses

*10%, **5%, ***1%—levels of significance (N = 1,288,982)

[a] Soil testing was only done in the saline belt. Therefore, the effect can be estimated only for districts in the coastal zone

[b] Relative effect, compared with the top panel

cities of Khulna and Barisal, in favor of destinations in India.[18] In contrast, we see that flooding has a slight negative effect on out-migration from the coastal region, and a slightly larger negative effect on inland districts, particularly those bordering India (Fig. 2).

Thus far, our interpretation of the migration effects has largely been in terms of vulnerability to flooding risk and moving constraints based on location. However, the observed migration patterns may also be in response to the perceived effects of flooding on the demand for labor at migrant destinations. A thorough investigation of the spatial correlation in labor market outcomes is beyond the scope of this paper, but we can provide some suggestive evidence by observing patterns in Figs. 1 and 2. Figure 1 illustrates how the effects of salinity associated with coastal flooding (e.g., due to typhoons, storm surge) are more likely to be widespread, potentially limiting the options for within-country migration as an adaptation strategy. In turn, flash flooding and riverbank erosion are relatively more common in the northern region, where the impacts appear heterogeneous, even within districts (Fig. 2). Thus, households may be inclined to access closer labor markets (relative to international labor markets) to diversify their income when faced with inundation risk. To examine the validity of this claim, we analyze the sample that excludes

[18] Recall, however, that our data on soil salinity cover only the coastal zone; therefore, our findings cannot be extrapolated to increased salinity outside these districts.

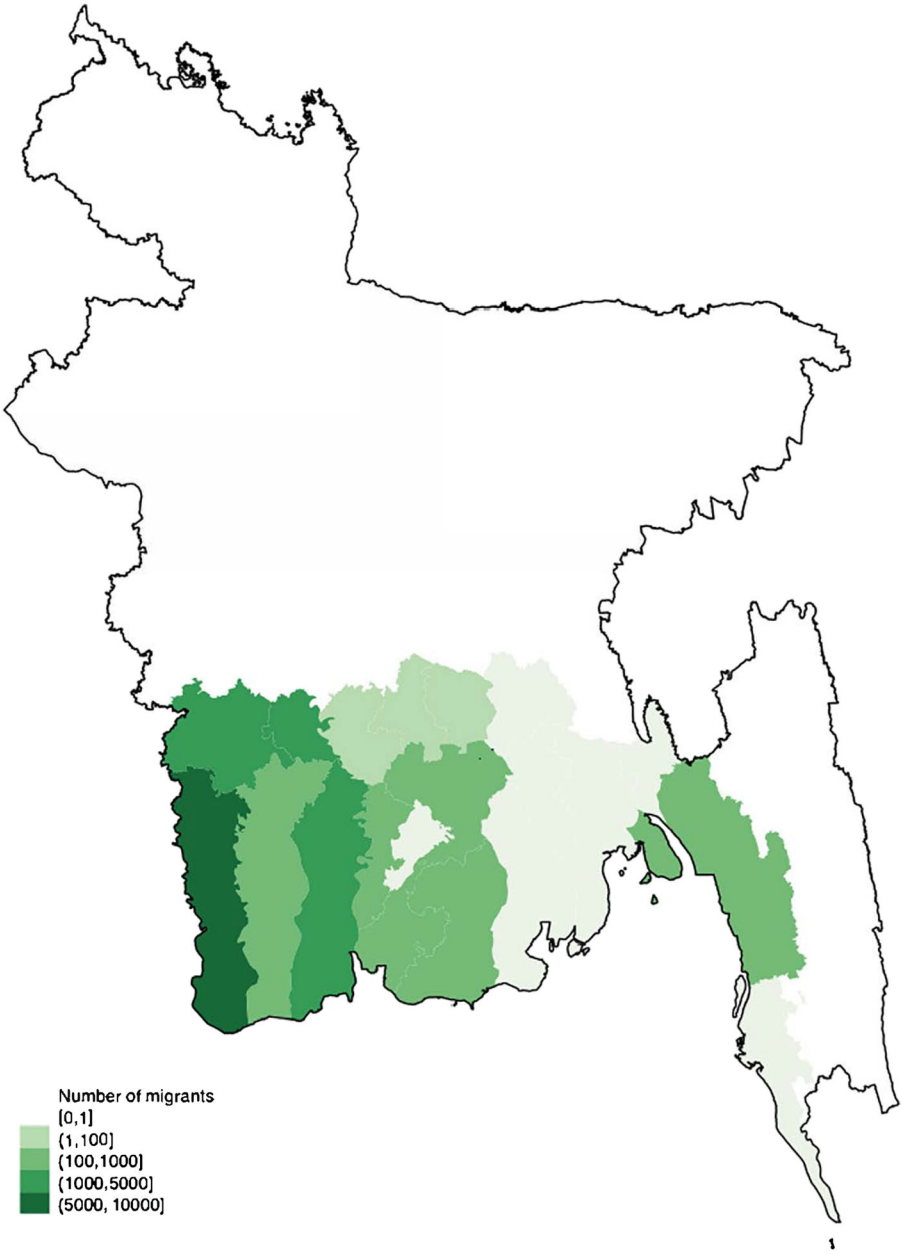

Fig. 1 Predicted change in the number of migrants from Bangladesh to India for a 1 standard deviation increase in soil salinity, coastal region only. *Note:* Model predicts a total of 17,874 more migrants moving to India in response to a 1 standard deviation increase in soil salinity

households reporting out-migrants within the country of Bangladesh. In panel D of Appendix 2, we see that the negative effect of flooding is even stronger for this group, which is consistent with substitution between internal and international migration when resources are constrained.

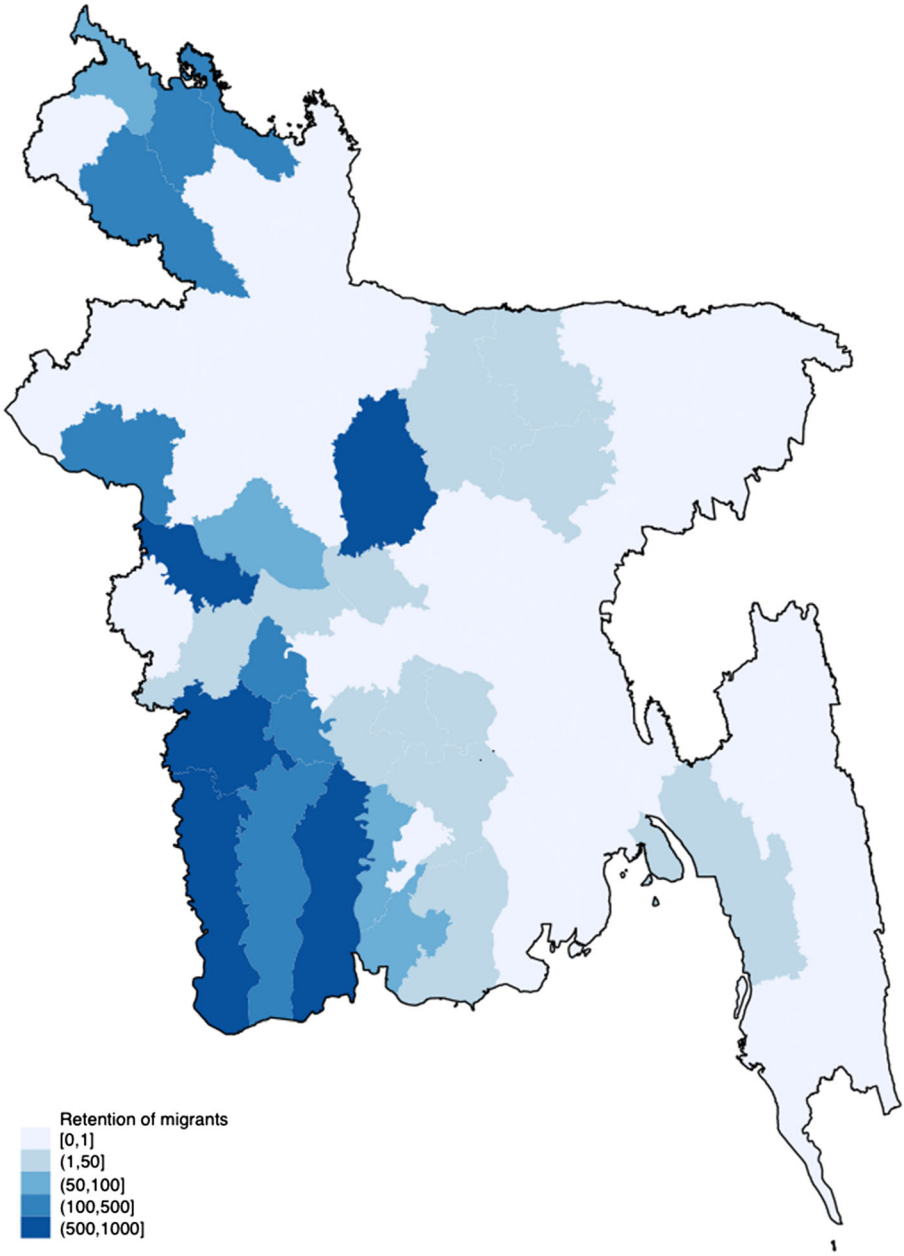

Fig. 2 Predicted change in the number of migrants from Bangladesh to India for a 1 standard deviation increase in flooding. *Note:* Model predicts a total of 5754 fewer migrants moving to India in response to a one-standard deviation increase in flooding

Household vulnerability to flooding-induced migration

We lastly examine how migration responses vary with household characteristics to test whether households endowed with human, social, or physical capital are more inclined

to use migration as an adaptation strategy (second hypothesis). The migration decisions of households with more males (at or below median sex ratio) and more members of prime working age (above median age ratio) are less responsive to environmental factors (Table 4, panels A and B). Higher than usual radiation and flooding has a smaller negative effect on the migratory responses of these groups, while salinity has a smaller positive effect. This contradicts the expected direction of these effects given migration is more likely conducive among individuals with greater transferable skills and fewer social constraints. Since these sub-groups do not appear to differentially take advantage of employment opportunities abroad, the empirical evidence rejects the second hypothesis posed in our conceptual framework. An alternative to the second hypothesis is that households prefer to adapt through investments on the farm (Chen and Mueller, 2018). Thus, families with a greater percentage of prime age males, for example, may exploit the human capital to adopt labor-intensive, local adaptation strategies in the face of environmental vulnerability than invest in migration.

We find no evidence that migration varies by the religion of the household head. Interestingly, the effects also do not differ substantially between migration to India and to the sub-continent region more broadly, suggesting that cross-border migration flows in this region are dictated primarily by geographic proximity rather than religious affinity.

To check for a wealth-differentiated migration effect, we compare the top quintile[19] to the bottom 80%, based on the asset index described above. A more muted response to increased soil salinity occurs among asset rich (top 20% of asset index) households (Table 4, panel C). While it is difficult to ascertain the specific reasons for these differences without more detailed data, these findings also refute our second hypothesis. They suggest that better endowed households are, on the whole, less likely to respond to salinity risk with international migration, perhaps due to their increased ability to diversify production practices (Khanom, 2016; Sovacool, 2018). Poorer households—with respect to demographic composition and wealth—are more likely to bear the high economic and social costs of international migration to adapt to gradual changes in soil salinity.

Although our main hypotheses focus on the role of flooding in cross-border migration, estimates of the heterogeneous effects also point to a net positive effect of an increase in minimum temperature on the migration of individuals among asset rich households. This is in direct opposition to the migration effects observed among the bottom 80% of the wealth distribution. One possible explanation for these findings is that the coping mechanisms available to combat heat stress remain relatively inaccessible or unsustainable. For example, drought-insurance programs continue to be piloted in areas of rather small geographic scale (Hill et al., 2019). Another illustration relates to farmers decreasing access to irrigated water for crop production during periods of heat stress, as increasing demand for groundwater depletes resources and increases water salinity. The fact that heat stress and salinity drive different demographic groups to migrate abroad suggests both cadres can take advantage of employment opportunities in countries adjacent to Bangladesh. The observed range of environmental patterns likely reflects the diverse investment portfolios by wealth and their unique set of income risks which ultimately underlie household migration decisions.

[19] We also compared households above and below the median for the asset index (results available upon request). Estimates were similar in sign but less precise, suggesting a steeper wealth gradient.

Table 4 Environmental migration patterns by household characteristics

	A. Sex ratio[a]		B. Age ratio[b]		C. Religion		D. Asset index[c]	
	Sub-continent	India	Sub-continent	India	Sub-continent	India	Sub-continent	India
Avg. min. temp.	0.802 (0.257)	0.780 (0.264)	0.844 (0.267)	0.765 (0.135)	0.611* (0.0848)	0.628* (0.0893)	0.727* (0.0706)	0.723* (0.0788)
Avg. max. temp.	0.889 (0.456)	0.775 (0.129)	0.860 (0.284)	0.783 (0.120)	0.850 (0.306)	0.849 (0.315)	0.879 (0.336)	0.815 (0.170)
Bright sun	0.580*** (1.18e−05)	0.607*** (0.000697)	0.625*** (7.94e−06)	0.648*** (0.000152)	0.787** (0.0391)	0.796* (0.0543)	0.698*** (3.46e−05)	0.655*** (5.81e−05)
Total precipitation	0.479*** (3.16e−05)	0.492*** (0.000178)	0.478*** (1.17e−06)	0.542*** (0.000143)	0.424*** (2.26e−06)	0.482*** (2.60e−05)	0.513*** (1.36e−06)	0.541*** (6.20e−05)
Flooded area	0.677*** (0.00152)	0.672*** (0.00384)	0.866 (0.157)	0.820* (0.0806)	0.793* (0.0578)	0.794** (0.0488)	0.855* (0.0736)	0.808** (0.0233)
Saline area	1.044*** (0.000528)	1.042*** (0.000871)	1.040*** (0.000149)	1.040*** (0.000192)	1.055*** (0.000862)	1.047*** (0.000893)	1.045*** (0.000146)	1.044*** (0.000197)
	Relative effects							
	At or below median[d]		Above median[d]		Head is Muslim[d]		Top 20%[d]	
Avg. min. temp.	1.026 (0.876)	0.985 (0.936)	0.885 (0.497)	0.983 (0.929)	1.533 (0.178)	1.354 (0.343)	2.370*** (0.00154)	2.184*** (0.00429)
Avg. max. temp.	0.991 (0.938)	1.085 (0.551)	1.076 (0.524)	1.095 (0.482)	1.036 (0.813)	0.929 (0.629)	0.817 (0.412)	0.739 (0.174)
Bright sun	1.216** (0.0389)	1.159 (0.184)	1.205** (0.0337)	1.140 (0.137)	0.821 (0.148)	0.825 (0.189)	0.951 (0.815)	1.498* (0.0644)
Total precipitation	1.062 (0.701)	1.227 (0.232)	1.117 (0.470)	1.106 (0.547)	1.282 (0.222)	1.301 (0.203)	0.921 (0.828)	1.473 (0.207)
Flooded area	1.427*** (0.00301)	1.334** (0.0381)	0.983 (0.886)	0.978 (0.875)	1.115 (0.491)	1.022 (0.892)	1.002 (0.988)	1.034 (0.821)
Saline Area	0.993 (0.153)	0.995 (0.418)	0.995 (0.363)	0.995 (0.378)	0.979 (0.178)	0.989 (0.395)	0.965** (0.0272)	0.968** (0.0282)

Notes: Socio-economic data drawn from Sample Vital Registration System, 2005–2011, Bangladesh Bureau of Statistics. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Saline soil represents the percentage of total upazila land area affected by saline contamination. Includes controls for historical soil salinity, rainfall, min/max temperature, sun, monsoon onset, demographic and wealth controls, region, and year-fixed effects. Negative binomial regression. Standard errors clustered at sub-district level. p values in parentheses

*10%, **5%, ***1%—levels of significance (N = 1,288,982)

[a] Calculated as number of female household members divided by total number of household members

[b] Calculated as number of household members age 35 or older divided by total number of members

[c] Constructed from principal components analysis. Includes water/energy sources and modern latrine

Conclusion

Climate change poses future risk to the livelihoods of farmers and the broader food security of Bangladesh. The aim of the paper was to understand the extent increased incidence of flooding may induce the flight of human capital and affect the future composition of the labor force. We formulated two hypotheses to incrementally test these separate effects.

The first hypothesis posited flooding, implicit in the increased exposure to inundation and soil salinity, increases the exodus of Bangladeshis to neighboring countries. We find that fewer Bangladeshis migrate to neighboring countries when the share of inundated land in their sub-district increases. On the other hand, 4% more Bangladeshis will move across the border with a one% increase in the share of saline-contaminated soil in their sub-district.

The second hypothesis indicated that households endowed with greater human, social, and physical capital are more prone to engage in cross-border migration as an adaptation strategy as the costs to migration are likely to be lower and benefits of securing employment higher than for other sub-populations. In fact, our findings reject this hypothesis. For example, the asset poor are, in fact, more responsive to flooding risk than other groups. Together these changes in environmental quality will shift the demographic composition, potentially compromising the supply of workers available to support the local economy. Beneficiaries of cheap, unskilled labor, for instance may be forced to contract their agricultural, service, or manufacturing production or invest in labor-saving technologies as workers from predominantly asset poor households leave the country.

A unique finding in this paper, though not central to the hypotheses of interest, was the vulnerability of asset rich households to fluctuations in minimum average temperature. This result echoes the importance of heat-induced crop failure on mobility in Bangladesh, first highlighted by Gray and Mueller (2012). In contrast with the earlier study, we, however, discover differential migratory responses by household wealth perhaps due to the greater range of migration, wealth, and climate observations represented by the vital registration data. The empirical results offer a new perspective on inclusion criteria when developing investment strategies to address the aforementioned risks. In particular, it is crucial to acknowledge risks faced by the poor *and* non-poor, as retention of the earnings, skills, and experience of the latter enhances national resilience.

The literature will begin to develop stylized facts around the fundamental drivers of migration, as scholars are able to take advantage of new efforts in the Global South to invest and disseminate data which monitors population movement over time. Our current study faces a few limitations which could be improved upon in future work. First, we lack confirmation of the duration of each event and, therefore, are unable to validate whether the moves are temporary or permanent. Second, the absence of spatial and temporal variation represented by our measure of soil salinity affects our ability to measure other important aspects of climate migration. By limiting the focus to changes in soil salinity over 5 years, for example, we are unable to express how mobility may be affected by seasonal or annual variations in soil salinity. Furthermore, the coarseness of our measure of salinity exposure affects our capacity to inform how policymakers should prioritize funding for adaptive investments. Soil salinity is likely a direct result

of changes in landscape and deforestation along the coast, sea level rise and storm surges, and groundwater management. It remains an open question which contributing factor to soil salinity is driving the mobility patterns observed in the paper. Future research would benefit from including more refined measures of soil salinity. In the short term, until maps of soil salinity become available for all vulnerable areas over time, policymakers may benefit from studies that demonstrate how migration patterns change in communities that receive interventions promoting resilience relative to similar communities lacking those investments. A few promising interventions being considered are the introduction of saline-tolerant varieties, the provision of stilt houses, and afforestation of mangroves in coastal areas.

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Appendix 1

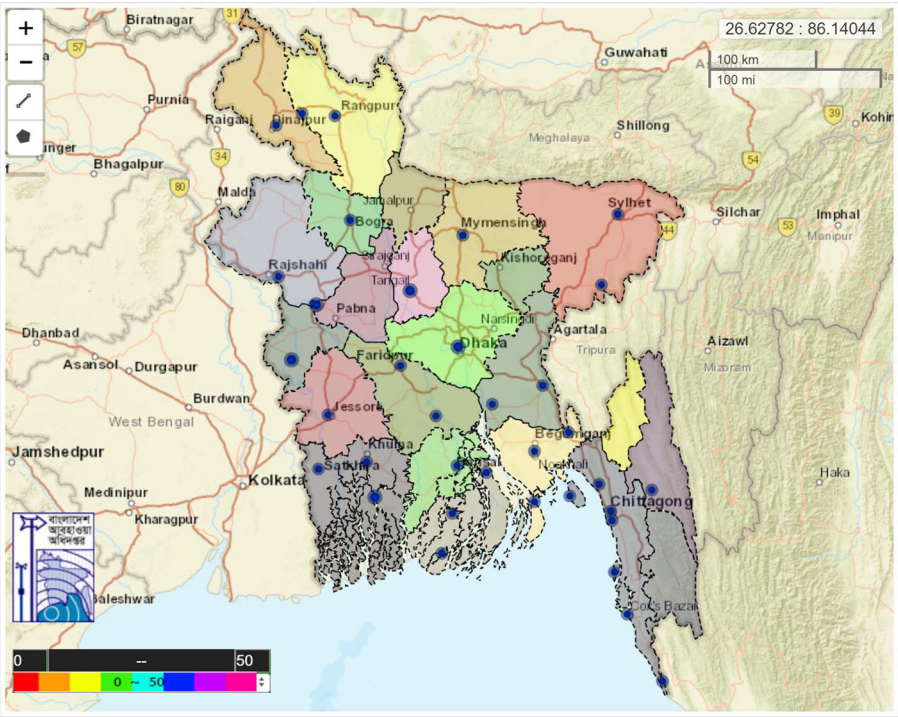

Fig. 3 Bangladesh Meteorological Department Weather Stations. Source: Bangladesh Meteorological Department, http://www.bmd.gov.bd

Table 5 Environmental migration patterns, separate time lags

	A. Sub-continent			B. India		
	1-year lag	2-year lag	3-year lag	1-year lag	2-year lag	3-year lag
Avg. min. temp.	0.856 (0.507)	0.931 (0.774)	0.958 (0.864)	0.869 (0.599)	0.822 (0.479)	1.013 (0.964)
Avg. max. temp.	0.878 (0.481)	0.734 (0.169)	1.347 (0.123)	0.743 (0.104)	0.769 (0.223)	1.404* (0.0833)
Bright sun	0.769*** (0.00151)	0.834*** (0.00487)	0.835 (0.117)	0.763*** (0.00408)	0.898 (0.128)	0.774** (0.0227)
Total precipitation	0.722* (0.0709)	0.661** (0.0366)	0.943 (0.661)	0.818 (0.314)	0.640* (0.0492)	0.965 (0.803)
Flooded area	0.804*** (0.00919)	0.890 (0.218)	0.936 (0.514)	0.754*** (0.00119)	0.868 (0.200)	0.881 (0.286)
Saline area[a]	1.039*** (0.000375)			1.039*** (0.000287)		

Notes: Socio-economic data drawn from Sample Vital Registration System, 2005–2011, Bangladesh Bureau of Statistics. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Saline soil represents the percentage of total upazila land area affected by saline contamination. Includes controls for historical soil salinity, rainfall, min/max temperature, sun, monsoon onset, demographic and wealth controls, region, and year-fixed effects. Negative binomial regression with effects reported as incidence rate ratios. Standard errors clustered at sub-district level. p values in parentheses

**5%; ***1%—levels of significance ate

[a] Only 1-year lag available

Table 6 Environmental migration patterns, alternate measures

	A. Indicator for migration[b]		B. Male migrants		C. Female migrants		D. Restricted sample[c]	
	Sub-continent	India	Sub-continent	India	Sub-continent	India	Sub-continent	India
Avg. min. temp.	0.679** (0.0283)	0.652** (0.0255)	0.795 (0.141)	0.734* (0.0749)	0.727 (0.113)	0.730 (0.109)	0.800 (0.185)	0.744 (0.116)
Avg. max. temp.	0.895 (0.417)	0.862 (0.327)	0.889 (0.362)	0.810 (0.152)	0.870 (0.387)	0.874 (0.428)	0.985 (0.903)	0.891 (0.416)
Bright sun	0.762*** (0.000218)	0.790*** (2.78e−05)	0.749*** (0.000121)	0.763*** (0.000463)	0.640*** (2.33e−05)	0.700*** (0.000499)	0.706*** (3.07e−05)	0.672*** (6.60e−05)
Total precipitation	0.539*** (1.65e−05)	0.604*** (0.000178)	0.500*** (3.84e−06)	0.590*** (0.000586)	0.483*** (3.56e−05)	0.531*** (0.000226)	0.536*** (2.55e−06)	0.577*** (0.000197)
Flooded area	0.921 (0.307)	0.869** (0.0407)	0.854* (0.0781)	0.775*** (0.00459)	0.880 (0.203)	0.867 (0.168)	0.832** (0.0260)	0.797** (0.0132)
Saline area[a]	1.026*** (0.000599)	1.025*** (0.000868)	1.033*** (0.000412)	1.032*** (0.000463)	1.041*** (0.000199)	1.040*** (0.000124)	1.038*** (0.000342)	1.038*** (0.000430)

Notes: Socio-economic data drawn from Sample Vital Registration System, 2005–2011, Bangladesh Bureau of Statistics. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Saline soil represents the percentage of total upazila land area affected by saline contamination. Includes controls for historical soil salinity, rainfall, min/max temperature, sun, monsoon onset, demographic and wealth controls, region, and year-fixed effects. Negative binomial regression with effects reported as incidence rate ratios. Standard errors clustered at sub-district level. p values in parentheses

*10%, **5%, ***1%—levels of significance (N = 1,288,982)

[a] Only 1-year lag available

[b] Logistic regression

[c] Excludes households with any internal (within country) migrants. N = 1,224,633

Table 7 Environmental migration patterns, multinomial logit

	Internal	India	Other South Asia	Mixed[b]
Avg. min. temp.	0.969 (0.538)	0.619** (0.0138)	0.840 (0.449)	1.059 (0.856)
Avg. max. temp.	0.953 (0.192)	0.937 (0.648)	1.318 (0.232)	0.463*** (0.000257)
Bright sun	0.936*** (0.00533)	0.788*** (2.68e−05)	1.156 (0.349)	0.680** (0.0266)
Total precipitation	0.965 (0.402)	0.612*** (0.000397)	0.543** (0.0241)	0.439*** (0.00416)
Flooded area	1.010 (0.632)	0.832*** (0.00820)	1.070 (0.744)	1.363 (0.188)
Saline area[a]	1.003 (0.208)	1.025*** (0.00199)	0.998 (0.928)	1.032*** (0.00261)

Notes: Socio-economic data drawn from Sample Vital Registration System, 2005–2011, Bangladesh Bureau of Statistics. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Saline soil represents the percentage of total upazila land area affected by saline contamination. Includes controls for historical soil salinity, rainfall, min/max temperature, sun, monsoon onset, demographic and wealth controls, region, and year-fixed effects. Multinomial logit regression with effects reported as relative risk ratios. Standard errors clustered at sub-district level. p values in parentheses

*10%, **5%, ***1%—levels of significance (N = 1,288,982)

[a] Only 1-year lag available

[b] Households with migrants to multiple destinations (internal, India, other South Asia)

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