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Coastal climate change, soil salinity and human migration in Bangladesh

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Climate change is not only altering weather patterns but also accelerating sea-level rise, leading to increased inundation and saline contamination of soils. Given projected sea-level rise, it is imperative to examine the extent to which farmers in coastal Bangladesh can adapt by diversifying economic activities before resorting to migration within and across borders. Here, to identify patterns in how households adapt to increased sea/freshwater flooding and soil salinity, we analyse nationally representative socioeconomic and migration data against a suite of environmental variables constructed at the sub-district level. Our results show that inundation alone has negligible effects on migration and agricultural production. However, gradual increases in soil salinity correspond to increasing diversification into aquaculture and internal migration of household members. Salinity is also found to have direct effects on internal and international migration even after controlling for income losses, with mobility restricted to certain locations within Bangladesh. Our study suggests that migration is driven, in part, by the adverse consequences of salinity on crop production.

In approximately 120 years, coastal areas, which are currently inhabited by 1.3 billion people, are projected to be inundated by sea-level rise[1], placing 40% of productive land in southern Bangladesh under severe threat[2]. However, recent studies show minimal migratory response to flooding[3–6]. Heavy monsoons lead to temporary displacement[5], but farmers return to their farms with delayed benefits on yields[3,7]. Many farmers have already adapted their cultivation practices to accommodate changes in inundation, given the frequency of flooding in this deltaic region. However, in coastal areas, the omission of soil salinity from empirical analyses may confound estimated flooding–migration relationships. Recent studies have highlighted the implications of salinity on agriculture given changes in the amplitude and frequency of sea-level extremes[8,9], and these effects are exacerbated by the paucity of available crop varieties that are tolerant to high-saline content[10].

We provide comprehensive quantitative analyses of the complex relationships between inundation, salinity, livelihoods and migration to characterize probable adaptation to gradual changes in sea level[11]. Several motivations for migration have been discussed in the literature, including expected income, social capital and aspirations[12]; we focus on the role of migration to reduce income risk for farm households, given that increases in flooding and salinity reduce agricultural income[13,14]. Our main hypothesis is that gradual increases in salinity (not flooding) will bear modest effects on migration until less costly adaptation strategies in the agricultural sector have been exhausted.

It is not a priori evident which locations will serve as migrant hubs. To minimize moving costs and remain close to family, individuals may move inland where the demand for agricultural labour is relatively unaffected by salinity. However, higher wages and denser labour markets may draw workers instead to urban areas. Finally, those with greater financial, human and/or social capital may decide to move internationally, as has been seen during periods of climatic stress[15]. To shed light on these patterns, we differentiate the effects of salinity (and flooding) on the probability of moving within and across countries and predict receiving destinations in Bangladesh based on existing migrant networks.

Socioeconomic data on migration are drawn from the Sample Vital Registration System (SVRS) of the Bangladesh Bureau of Statistics, covering 147 coastal sub-districts from 2003 to 2011 (Methods). Migration information is reported by households for any individuals who have been away for at least six months or have left because of household partition or marriage. Our final household–year sample is 550,473. Having an internal migrant (5.2%) is more prevalent than having an international migrant (0.8%) (Supplementary Table 1).

Agricultural production data are taken from the Household Income and Expenditure Surveys (HIES) of the Bangladesh Bureau of Statistics in 2005 and 2010. The HIES are repeated cross-sectional surveys, which collect information from distinct households over time. Our sample is limited to those households that reported any self-employment activity in crop production (42% and 44% for 2005 and 2010, respectively). Livelihood variables include total farm revenue and its components, crop revenue and the share of revenue from aquaculture. Average farm revenue is 37,740 Bangladeshi Taka (in 2005) (Supplementary Table 1). Among the 40% of crop farmers who diversify into aquaculture, 37% of their total revenue is derived from fish production.

To identify flooding, we used data from NASA's MODIS (Moderate Resolution Imaging Spectro-radiometer) satellite to construct the Modified Normalized Difference Water Index (MNDWI)[16] (Methods). The MNDWI provides the most accurate detection of flooded areas compared to other commonly used band-ratio indices and has the most stable threshold[17,18]. Measurements of soil salinity are based on 2,500 samples collected in field surveys conducted throughout the coastal region (excluding the protected Sundarbans area) by the Soil Resource Development Institute[19] (Methods). Our preferred measure is the percentage of land area in each sub-district with saline contamination, defined as electrical conductivity of $\geq 2.0\,\mathrm{dS\,m^{-1}}$.

We used a linear regression model in which agricultural production (crop revenue, total farm revenue and share of farm revenue earned from aquaculture) is a function of soil salinity and

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Table 1 | Effect of flooding and soil salinity on farm revenue in the coastal zone

	Crop revenue (Tk)				Aquaculture revenue (%)				Total revenue (Tk)			
Model	**I**	**II**	**III**	**IV**	**I**	**II**	**III**	**IV**	**I**	**II**	**III**	**IV**
Inundated area	1,179	1,390			0.00105	−0.00109			4,719	4,503		
	(1.116)	(1.344)			(0.114)	(−0.118)			(1.334)	(1.302)		
Saline soil		−123.6**				0.00125*				126.7		
		(−2.069)				(1.849)				(0.701)		
Inundated area (Q2)			−582.9	−501.8			0.0167	0.0148			1,883	1,663
			(−0.224)	(−0.193)			(0.701)	(0.627)			(0.388)	(0.340)
Inundated area (Q3)			−1,398	−1,239			0.0531**	0.0515**			−367.0	−460.8
			(−0.468)	(−0.421)			(2.440)	(2.363)			(−0.0759)	(−0.0969)
Inundated area (Q4)			−380.2	460.4			0.0105	−0.00101			−2,961	−3,911
			(−0.127)	(0.151)			(0.401)	(−0.0376)			(−0.526)	(−0.637)
Inundated area (Q5)			2,395	2,809			0.0219	0.0163			9,191	8,976
			(0.758)	(0.877)			(0.957)	(0.674)			(1.453)	(1.407)
Saline soil (Q2)				−4,763*				0.0201				−7,033
				(−1.757)				(0.793)				(−1.237)
Saline soil (Q3)				−676.7				0.0300				2,531
				(−0.271)				(1.553)				(0.543)
Saline soil (Q4)				−4,385				0.0633**				6,575
				(−1.339)				(2.097)				(0.734)
Saline soil (Q5)				−9,123**				0.0760*				−92.35
				(−2.277)				(1.715)				(−0.00850)
n	2,554	2,554	2,554	2,554	2,554	2,554	2,554	2,554	2,554	2,554	2,554	2,554

Socioeconomic data drawn from HIES, 2005 and 2010, 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 that is affected by saline contamination. Model I includes all control variables and inundated area. Model II includes the same variables as Model I, adding the soil salinity variable. Model III replaces the inundated area variable in Model I with four variables indicating whether the inundation values lie in the second, third, fourth and fifth quintiles to allow for nonlinear flooding effects on outcomes. Model IV replaces the inundated area and soil salinity variables in Model II with eight variables indicating whether inundation and soil salinity values lie in the second, third, fourth and fifth quintiles to allow for nonlinear flooding and soil salinity effects on outcomes. All models include controls for historical soil salinity, rainfall, minimum and maximum temperature, sun, monsoon onset, demographic and wealth controls, year fixed effects. Standard errors are clustered at the sub-district level. *t*-statistics are shown in parentheses. Q, quintile; Tk, Bangladeshi Taka. $^*P<0.1$; $^{**}P<0.05$.

flooding. We used a linear probability model (LPM) to assess the effect of flooding and soil salinity on the likelihood that a household has at least one internal or international migrant. To account for the delayed effect of flooding, the measure is lagged by one year. In addition, to account for underlying differences in the risk of flooding, we standardize the measure by the sub-district specific mean and standard deviation (s.d.). For both specifications, we explore non-linear effects by replacing the continuous measurements of flooding and salinity with indicators for whether the values of the variables lie within the second, third, fourth and fifth quintiles of the sample. Additional controls include historical soil salinity; household demographics and wealth; lagged measurements of environmental exposure correlated with crop production[20] (precipitation, minimum/maximum temperatures, bright sun exposure and monsoon onset); and a time fixed effect τ_t (see Methods for detailed description of specifications).

Soil salinity has a significant negative effect on total annual crop revenue (Table 1). An increase of 1 s.d. in the percentage of saline-contaminated land reduces total crop revenue by nearly 3,500 Bangladeshi Taka, or roughly 0.1 s.d. Allowing for non-linearity shows that this effect, however, is concentrated in the second and fifth quintiles. The tolerance of crops to moderate levels of salinity may be attributable to complex relationships between salinity, microbial composition and plant growth[21,22]. Flooding is found to have no significant effect on total crop revenue and the flooding coefficients change minimally with the addition of the salinity variables.

The percentage of household revenue from aquaculture (Table 1) is positively affected by extreme (quintiles 4 and 5) salinity. Moving from the first to the fourth quintile increases the percentage of revenue derived from aquaculture by 6.3 percentage points, equivalent to about 0.3 s.d. We observe a more pronounced shift toward aquaculture among those engaged in crop and fish production (Supplementary Table 3). Notably, we find no significant effect of salinity on total farm revenue (Table 1), despite the sizable and significant effects on crop revenue. These results together suggest that households shift towards aquaculture as salinity compromises

Table 2 | Effect of flooding and soil salinity on household-level migration in the coastal zone

	Internal					International				
Model	**I**	**II**	**III**	**IV**	**V**	**I**	**II**	**III**	**IV**	**V**
Inundated area	0.00131	0.00134				-4.30×10^{-5}	-5.43×10^{-5}			
	(1.169)	(1.202)				(−0.171)	(−0.209)			
Saline soil		0.000166*					-7.26×10^{-5}**			
		(1.782)					(−2.593)			
Inundated area (Q2)			−0.00492	−0.00436	−0.00103			−0.000120	−0.000221	0.000272
			(−1.066)	(−0.930)	(−0.257)			(−0.114)	(−0.212)	(0.236)
Inundated area (Q3)			−0.00332	−0.00316	0.000870			0.000418	0.000329	0.000460
			(−0.758)	(−0.739)	(0.220)			(0.473)	(0.367)	(0.475)
Inundated area (Q4)			−0.00403	−0.00367	−0.00238			0.000135	4.43×10^{-5}	0.000192
			(−1.437)	(−1.346)	(−0.834)			(0.161)	(0.0508)	(0.203)
Inundated area (Q5)			0.000958	0.000975	0.00225			−0.000116	−0.000185	9.61×10^{-5}
			(0.239)	(0.251)	(0.551)			(−0.142)	(−0.226)	(0.103)
Saline soil (Q2)				0.0160**	0.0152*				−0.00256	−0.00315
				(2.189)	(1.835)				(−1.157)	(−1.235)
Saline soil (Q3)				0.00330	− 0.000805				−0.00235	−0.00213
				(0.609)	(−0.128)				(−1.302)	(−0.955)
Saline soil (Q4)				0.00485	0.00255				−0.00407**	−0.00451**
				(0.806)	(0.372)				(−2.217)	(−2.110)
Saline soil (Q5)				0.0136**	0.00606				−0.00534***	−0.00457*
				(2.061)	(0.766)				(−2.814)	(−1.811)
Predicted revenue					0.110*					-2.06×10^{-5}
					(1.933)					(−1.000)
n	550,473	550,473	550,473	550,473	513,389	550,473	550,473	550,473	550,473	513,389

Socioeconomic data were drawn from SVRS, 2003–2011, 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. Model V includes the same variables as Model IV, adding predicted revenue. All models include controls for historical soil salinity, rainfall, minimum and maximum temperature, sun, monsoon onset, demographic and wealth controls, year fixed effects. A LPM was used. Standard errors are clustered at sub-district level. *t*-statistics are shown in parentheses. Q, quintile. $^{*}P<0.1$; $^{**}P<0.05$; $^{***}P<0.01$.

crop production. Moreover, this substitution appears to be effective in mediating income risk owing to flooding and soil salinity, at least with respect to agricultural production.

Soil salinity is found to have large and significant, but heterogeneous, effects on migration (Table 2). An increase of 1 s.d. in the percentage of saline-contaminated soil increases (decreases) the likelihood of internal (international) migration by 0.43 (0.19) percentage points. However, the continuous measure again masks significant heterogeneity in responses to salinity. Households are more likely to engage in internal migration when faced with either slight (quintile 2) or extreme (quintile 5) soil salinity (Table 2). The similarities between the results for crop revenue and internal migration are striking, with salinity effects for both outcomes being large and statistically significant only in the second and fifth quintiles. Going from quintile 1 to quintile 2 (or 5) for soil salinity increases the likelihood of internal migration by 1.6 (or 1.36) percentage points, a very large effect compared to 5.12% of households reporting an internal migrant within the last year. Moves are mostly to rural areas and are more pronounced in areas with above-median river density (Supplementary Table 3).

Conversely, only extreme salinity (quintiles 4 and 5) has a negative effect on the likelihood of international migration; going from quintile 1 to quintile 4 (or 5) for salinity decreases international migration by 0.41 (or 0.53) percentage points, again a large effect compared to the sample mean of 0.76% (Table 2). The similarities between these results and those for aquaculture are remarkable, suggesting that international migration may be a substitute for the conversion of crop production to aquaculture. This is consistent with narratives of aquaculture offering new local employment opportunities[23], perhaps reducing the gains among those who would typically migrate abroad for additional income. The stark differences for internal and international migration indicate that these are very different adaptation mechanisms and should not be conflated in assessing resilience. Moreover, among international moves, we see that moves within South Asia respond to flooding and salinity similarly to moves within the country, suggesting

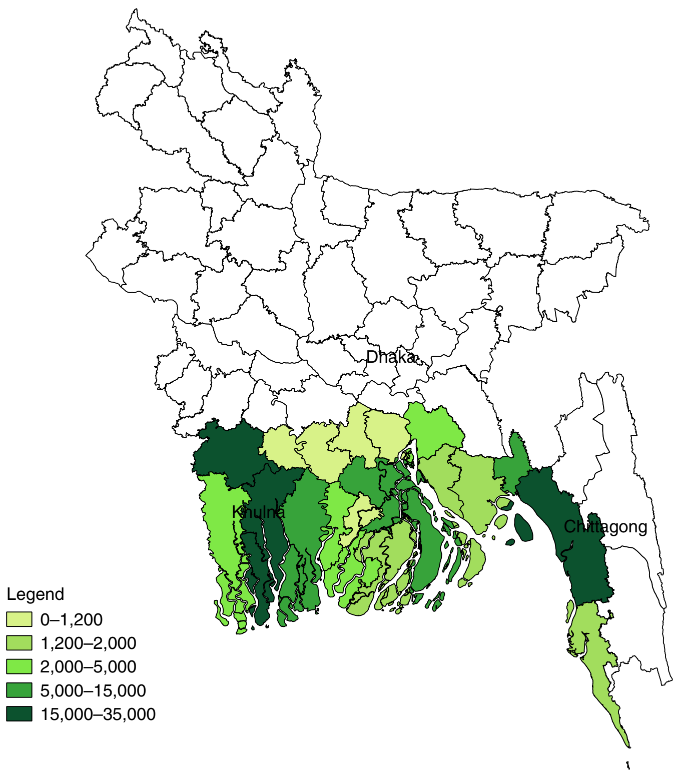

Fig. 1 | Projected additional within-district migrants in coastal region of Bangladesh because of an increase in salinity from the first to fifth quintile. Projections are based on the within-district flows of the population computed from the 2002 SVRS. The number of additional migrants is calculated by multiplying the flows by the incidence rate ratio estimated using the negative binomial regression model presented in Supplementary Table 3. Given existing historical migration patterns, the total number of additional within-district migrants moving from a scenario of low salinity to a scenario of extreme salinity would be 138,025 people.

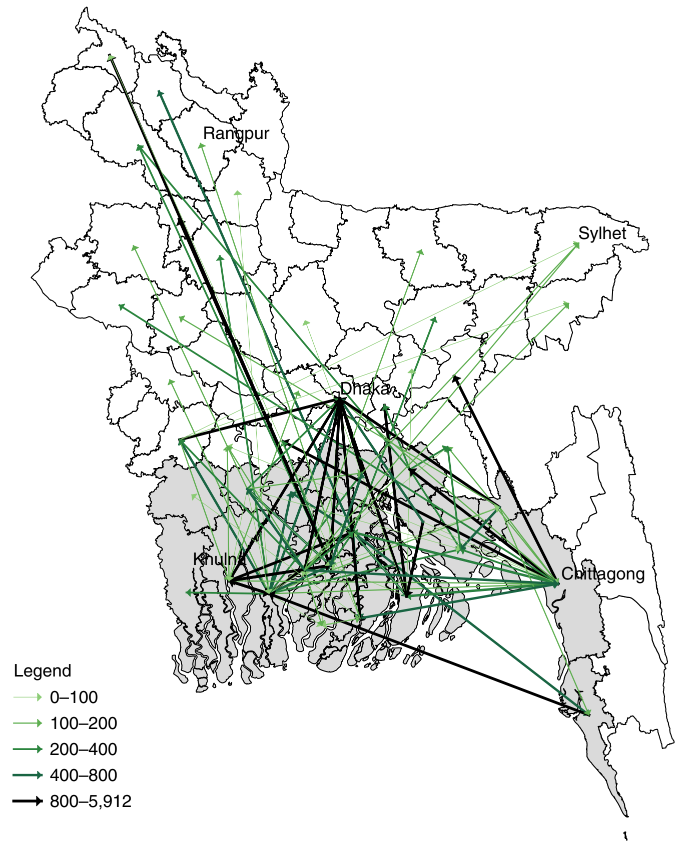

Fig. 2 | Projected additional out-of-district migrants from coastal region of Bangladesh because of an increase in salinity from the first to fifth quintile. Projections are based on the bilateral district flows of the population computed from the 2002 SVRS. The number of additional migrants is calculated by multiplying the flows by the incidence rate ratio estimated using the negative binomial regression model presented in Supplementary Table 3. Given existing historical migration trends, the total number of additional out-of-district migrants moving from a scenario of low salinity to a scenario of extreme salinity would be 57,861 people.

that migration costs may be more salient than national borders (Supplementary Table 4).

Using predictions from a negative binomial regression model of the number of internal migrants (Supplementary Table 3) and assigning locations based on 2002 population migration flows, Figs. 1 and 2 illustrate the number and destinations of internal migrants under a scenario in which salinity increases from the first to the fifth quintile, holding all other features of the household and environment constant. Figure 1 highlights the spatial distribution of migrants that would remain within a district according to historical migration patterns. Approximately 140,000 people would respond to the rise in salinity by moving to another location within their original district. The majority are in districts that house a major city, such as Khulna and Chittagong. Figure 2 highlights the projected flows of around 60,000 coastal inhabitants to alternative districts. Relatively few migrate to areas in the north. More systematically, migrants enter Dhaka and then neighbouring districts in the coastal region.

Although households seem able to largely offset crop income losses by increasing production in aquaculture, the effects of soil salinity are concentrated in the second and fifth quintiles for both crop revenue and internal migration. To test more directly for a link between the two, we estimate an expanded specification that includes the predicted value of average farm revenue at the sub-district level (Methods). If the direct effects of flooding and/or salinity disappear after the addition of this variable, then we can infer that environmental migration is primarily driven by the influence of salinity and flooding on agricultural income.

In Table 2, the effect of mild salinity (quintile 2) continues to be positive and significant, and the point estimate is almost unchanged by the inclusion of predicted revenue. The coefficient for quintile 5 is no longer significant, and the point estimate is much smaller in magnitude. This suggests that, in the face of extreme soil salinity, income losses are the primary motive for internal moves, whereas mild salinity has a direct effect on migration decisions. We also find a positive and significant coefficient on predicted revenue, which confirms that households engage in internal migration when they have greater resources to overcome liquidity constraints.

Conversely, in the case of international migration, both quintiles 4 and 5 for soil salinity continue to have a significant negative effect, even after controlling for predicted revenue. Therefore, extreme salinity appears to have a direct effect on international migration, even conditional on income shocks. Moreover, predicted revenue is found to have no significant effect, and the point estimate is small in magnitude. International migration may be more responsive to pull factors, again highlighting the need to distinguish between internal and international moves.

The gradual rise in sea level, combined with increasing frequency of catastrophic storms will leave the coastal population of Bangladesh vulnerable to inundation. Subsidence will cause another 10–18 mm of relative sea-level rise per year[24]. Scant attention has been devoted to how the gradual inundation of coastal lands affects livelihoods with respect to saline intrusion. Our results suggest that future work should consider a broader range of measurements to establish the robustness of estimated relationships between flooding and socioeconomic outcomes. In particular, soil salinity leads to increased migration within the country. In part, internal mobility driven by increases in soil salinity can be explained by its contributions to agricultural income losses. When focusing on international mobility, we find the opposite effect, with extreme soil salinity having a large negative effect. The relative attractiveness of new employment related to fish farming may deter would-be international migrants[23]. Overall, liquidity constraints limit moves over short distances (a trapped populations dynamic[25]), raising concerns that the most vulnerable households may be the least resilient in the face of climate change.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, statements of data availability and associated accession codes are available at https://doi.org/10.1038/s41558-018-0313-8

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Author contributions

J.C. and V.M. designed the evaluation, constructed the datasets and wrote the paper. J.C conducted the migration and livelihood impact analysis, while V.M. contributed the visual projections based on the migration modelling.

Competing interests

The authors declare no competing interests.

Additional information

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Methods

Data and sample description. The districts included in the analysis are: Satkhira, Jessore, Narail, Gopalganj, Khulna, Bagerhat, Pirojpur, Barguna, Jhalokati, Patuakhali, Barisal, Bhola, Shariatpur, Chandpur, Noakhalim, Feni, Lakshmipur, Chittagong, Cox's Bazar and Madaripur. The SVRS is an intercensal survey conducted annually to provide nationally representative population statistics at the district level. A dual record system is used, combining contemporaneous event reports to the Local Registrar with quarterly reporting to the sub-district statistical office. This ensures accurate and comprehensive reporting of major vital statistics, including births, deaths, marital changes and migration. Sampling is done first at the locality level, to achieve representation across rural, urban and metropolitan areas. Primary sampling units (PSUs) are then selected within each strata to achieve representation across districts, and 200 households are selected within each of the 1,000 PSUs to create a sample of approximately 200,000 households and 1 million individuals in each year, with roughly 30% of the sample in the coastal region.

From the SVRS data, we construct the following demographic and wealth variables to include as explanatory factors of migration broadly: literacy, religion, age (quadratic) of the household head; the number of household members; the number of household members in eight age–sex categories (number of male and female household members that were 0–5 years old, 6–16 years old, 17–54 years old and greater than 54 years old); indicators for whether the household has improved water and latrine facilities (primary water source comes from tap, primary water source comes from well, secondary water source comes from tap, secondary water source comes from well, has its own water source and has modern or sanitary latrine); and sources of energy (has kerosene as a source of light, has electricity as a source of light, has kerosene as a source of fuel, has electricity as a source of fuel and has gas as a source of fuel). Descriptive statistics of the household sample created from the SVRS data are provided (Supplementary Table 1). An important limitation of these data is that migration is only recorded for individuals who have left the household permanently. Directing attention to long-term, individual migration may lead to underestimates of the true number of environmental migrants, since cases in which entire households or communities have already been displaced are left undocumented. Short-term migration is also excluded from our analysis.

The HIES survey is the primary tool for assessing the socioeconomic status of the Bangladeshi population. The sampling structure is similar to that of the SVRS, stratified first at the locality and then at the district level. Given the more detailed survey mechanism, only 612 PSUs are selected and only 20 households within each PSU, creating a sample of just over 12,000 households per year. A unique feature of the HIES is that surveying is done over the course of a complete year, to accurately characterize seasonal fluctuations in income, expenditure and consumption. In 2010, several new modules were added, including one on migration and remittances. However, to maintain comparability with the 2005 survey and the SVRS, we limit attention to household demographics and basic socioeconomic indicators. We create the following explanatory variables to include in the income/fish diversification statistical models: age (quadratic), literacy, education, marital status and religion of the household head; the number of household members in the same eight age–sex categories; home construction materials and size (whether walls are made of brick, wood, mud, or bamboo; whether the roof is made of cement, wood, tile or bamboo; number of rooms); amount of agricultural land; and indicators for improved water (piped, tube well, pond/river, well and spring) and latrine (sanitary, water seal, pit, permanent kacha and temporary kacha) facilities and access to electricity (Supplementary Table 1).

NASA's MODIS satellite provides data on inundation. Each pixel in an image represents an area of 500 m^2, and data are aggregated into eight-day composites that provide the best possible observation during the period. A pixel is defined as water if the MNDWI value exceeds 0.1, and sub-district level measurements are based on the maximum percentage of water pixels over all eight-day composites in the period. To differentiate water bodies from flooding, we look at the difference in water coverage between the monsoon (July–December) and dry (January–March) seasons within each year. One limitation of MODIS imagery is that the optical sensors are unable to penetrate cloud cover, which is particularly problematic for determining flooding during the monsoon season. Synthetic aperture radar images have the ability to penetrate clouds but are substantially more limited in their geographic and temporal coverage. However, measurements derived from MODIS imagery exhibit a very strong correlation ($R^2 = 0.96$) with measurements derived from synthetic aperture radar imagery in Bangladesh[26]. Soil samples were only collected in 2000 and 2009 owing to the high cost of collection and testing. Our salinity variable therefore takes on the 2009 value for all years 2006–2010, inclusive, and the 2000 value for the years of 2002–2005.

All statistical models account for additional elements of environmental exposure. Data on rainfall are derived from NASA's Tropical Rainfall Measuring Mission (TRMM), which provides precipitation estimates on a 0.25 × 0.25° grid. Although in situ data are available from a large network of over 500 rain gauges maintained by the Bangladesh Water Development Board, over one-third of the gauges have 30 or more missing observations within a single year, compromising the accuracy of total precipitation measurements. Imputation with neighbouring stations can also be problematic, given substantial variability across microclimates. Conversely, owing to sensitivity limitations, only moderate to high rainfall rates can be detected with satellite imagery[27]. Consequently, although the correlation between daily TRMM data and rain gauge data is found to exceed 0.90 for Bangladesh, TRMM measurements tend to overestimate precipitation during the pre-monsoon period and in dry regions and underestimate precipitation during the monsoon period and in wet regions[28]. To address this, we use the monthly precipitation estimates of TRMM, which combine the aggregated three-hourly multisatellite products with rain gauge data and have been found to have the highest degree of accuracy[26].

Daily data on temperature and monthly data on bright sun exposure are drawn from the weather stations of the Bangladesh Meteorological Department. In total, the Bangladesh Meteorological Department maintains 34 stations around the country, with roughly one station per district (the map of weather stations is available upon request from the corresponding authors). In the case of missing observations, data are imputed from the closest station. We use daily rainfall measurements from the 500 or more weather stations of the Bangladesh Water Development Board to identify the onset of the monsoon, which has been shown to affect agricultural yields in this region[29]. Data from the 34 stations of the Bangladesh Meteorological Department are used in the case of missing observations. We define the monsoon onset date as the first date after 1 May on which there has been 'three or more consecutive days of rainfall, with daily rainfall of 5 mm or more'[30]. Because we lack access to wind data, we are unable to account for southerly or southeasterly winds in our measurements[30]. Therefore, our measurements will tend to produce an earlier onset date than is more favourable for rice production.

Onset of the monsoon is normalized to be the deviation from the mode onset date for the region over the previous 30 years. Inundation measurements are normalized by the mean and s.d. within the study period. All other environmental factors (rainfall, temperature and sunlight) are standardized by the 30-year mean and s.d. This approach is in lieu of using level versions of the environmental variables in a regional fixed-effects model, as the focus on coastal salinity intrusion limits both the temporal coverage and spatial variation in our environmental variables.

Main specifications. To examine how salinity (S) and flooding (F) influence agricultural income, we used the following linear regression model:

$$\begin{aligned} Y_{hjt} = {} & \beta Z_{hjt} + \delta X_{hjt-1} + \theta_F F_{jt-1} \\ & + \theta_S S_{jt-1} + \theta_S^{88} S_{j,1988} + \tau_t + \mu_{hjt} \end{aligned} \tag{1}$$

where Y represents annual crop revenue, total farm revenue and the share of farm revenue earned from aquaculture. Flooding is lagged and standardized by the sub-district specific mean and s.d. We replace our continuous measurements of flooding and salinity with indicators for whether the values of these variables lie within the second, third, fourth and fifth quintiles of the sample to examine non-linear effects on migration. All specifications control for historical S (1988), as a proxy for underlying risk of saline intrusion; a vector of household demographic and wealth variables $\mathbf{Z}$; a vector of lagged measurements of environmental exposure correlated with crop production $\mathbf{X}$ (precipitation, minimum/maximum temperatures, bright sun exposure and monsoon onset); and a time fixed effect τ_t.

We relate whether the household has at least one internal migrant or international migrant to flooding and salinity using a LPM:

$$\begin{aligned} M_{hjt} = {} & \alpha W_{hjt} + \gamma X_{hjt-1} + \beta_F F_{jt-1} \\ & + \beta_S S_{jt-1} + \beta_S^{88} S_{j,1988} + \rho_t + \varepsilon_{hjt} \end{aligned} \tag{2}$$

As with the agricultural outcomes, we used both the continuous measurements of flooding and soil salinity as well as the quintile categories, lagged by one year. All environmental variables used in the linear regression model are also included in $\mathbf{X}$, as well as a time fixed effect ρ_t. The household explanatory variables implicit in $\mathbf{W}$ are similar but do not entirely overlap with those in $\mathbf{Z}$ owing to the use of a different secondary data source. Both the linear regression model and LPM estimate clustered standard errors at the sub-district level.

Specification for testing the role of agricultural losses on migration. To determine whether agricultural income losses are the primary mechanism that underlies the environmental migration responses, we re-estimate the LPM adding a control for predicted farm revenue ($\hat{\pi}$) at the sub-district level. Because farm revenue must be drawn from a different data source with different explanatory variables, we cannot generate household-specific predictions from the linear regression model. Instead, we combine the regression-adjusted sub-district average with the annual variation owing to flooding and salinity. This can be understood as a proxy for local agricultural earnings that reflects both changes in revenue for cultivators and changes in wages for labourers. To estimate the sub-district average, we run a sub-district fixed-effects regression (FE) of total household farm revenue on the environmental variables, including flooding and salinity, and year dummy variables:

$$Y_{hjt} = \delta^{\mathrm{FE}} X_{hjt-1} + \theta_F^{\mathrm{FE}} F_{jt-1} + \theta_S^{\mathrm{FE}} S_{jt-1} + \sigma_{jt} + \tau_t^{\mathrm{FE}} + \epsilon_{hjt} \quad (3)$$

The suggested sub-district fixed effects ($\hat{\sigma}$) reflect the region-specific average, net of aggregate time-varying shocks and environmental conditions. We then use the linear regression model to predict only the variation in revenue due to flooding and salinity and add this to the sub-district fixed effect.

$$\hat{\pi}_{jt} = \hat{\sigma}_{jt} + \hat{\delta} X_{hjt-1} + \hat{\theta}_F F_{jt-1} + \hat{\theta}_S S_{jt-1} \quad (4)$$

Given that the additional regressor ($\hat{\pi}$) in the LPM is a predicted variable, we bootstrap the expanded LPM model using 1,000 replications to formulate the coefficient standard errors, maintaining the clustering at the sub-district level. Owing to incomplete overlap in regions between the two data sources, we are unable to compute predicted revenue values for 7.7% of households in the SVRS. Therefore, we present the results of the LPM on the limited sample to alleviate concerns about selection (Supplementary Table 5).

Data availability

The datasets generated during the current study and Stata dofiles utilized in the analysis are available upon request from the corresponding authors.

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