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Disruption, not displacement: Environmental variability and temporary migration in Bangladesh

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Abstract

Mass migration is one of the most concerning potential outcomes of global climate change. Recent research into environmentally induced migration suggests that relationship is much more complicated than originally posited by the ‘environmental refugee’ hypothesis. Climate change is likely to increase migration in some cases and reduce it in others, and these movements will more often be temporary and short term than permanent and long term. However, few large-sample studies have examined the evolution of temporary migration under changing environmental conditions. To address this gap, we measure the extent to which temperature, precipitation, and flooding can predict temporary migration in Matlab, Bangladesh. Our analysis incorporates high-frequency demographic surveillance data, a discrete time event history approach, and a range of sociodemographic and contextual controls. This approach reveals that migration declines immediately after flooding but quickly returns to normal. In contrast, optimal precipitation and high temperatures have sustained positive effects on temporary migration that persist over one to two year periods. Building on previous studies of long-term migration, these results challenge the common assumption that flooding, precipitation extremes and high temperatures will consistently increase temporary migration. Instead, our results are consistent with a livelihoods interpretation of environmental migration in which households draw on a range of strategies to cope with environmental variability.

1. Introduction

Among the potential social costs of climate change, involuntary human migration is one of the most discussed and feared. A common framing envisions the mass displacement of large numbers of vulnerable “environmental refugees” who move permanently to distant

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destinations (Myers, 2002). However, this narrative is increasingly being challenged by a growing body of empirical research which finds that climatic effects vary considerably over space and can even reduce migration by removing necessary household resources (Bohra-mishra et al., 2014; Gray and Mueller, 2012; Gray and Wise, 2016; Gray and Mueller, 2012; Hunter et al., 2013; Mueller et al., 2014; Nawrotzki and Bakhtsiyarava, 2016). Largely lost in this debate is the fact that the vast majority of population mobility occurs over small spatial and temporal scales, movements which are difficult or impossible to measure with traditional large-sample data sources (Coffey, Papp, & Spears, 2015). These short-distance and short-term moves are an element of many sustainable household livelihood strategies in low-income countries (Ellis, 2000) have also been noted anecdotally to serve as important coping strategies for environmental shocks (McLeman & Hunter, 2010).

To examine this complex relationship, our analysis builds on a growing number of studies that have linked large-sample migration data sources to external environmental datasets in order to measure environmental effects on migration while controlling for potential confounders (Fussell, Hunter, & Gray, 2014). This approach advances on earlier approaches by addressing the multicausal nature of migration, recognizing that environmental shocks can contribute to "everyday mobility", and avoiding the need to label a subset of migrants as environmentally-induced (Martin et al., 2014; Scoones, 2000). Similar techniques have been used to investigate the effects of climatic variability (Bohra-mishra et al., 2014; Gray and Mueller, 2012b; Henry et al., 2004; Hunter et al., 2013; Jennings and Gray, 2014; Mueller et al., 2014; Nawrotzki and Bakhtsiyarava, 2016), natural disasters (Gray and Mueller, 2012a; Gray et al., 2014; Halliday, 2006), and land quality (Gray, 2011; Gray & Bilsborrow, 2014; Hunter et al., 2014). To date, however, only a handful of studies used these approaches to investigate short-term migration (Gray, 2011; Hunter et al., 2014), incorporated high-frequency data from demographic surveillance sites (Hunter et al., 2014; Jennings & Gray, 2014), or applied these approaches in South Asia (Gray and Mueller, 2012a; Mueller et al., 2014), despite the region's well-deserved reputation for vulnerability to environmental shocks (IOM, 2010).

To address these substantive and methodological gaps, we link demographic surveillance data on temporary migration from Matlab, Bangladesh for 200,000 individuals over an 18-year period to monthly biophysical data on riverine flooding, temperature, and precipitation. This socio-environmental dataset allows us to estimate discrete-time event history models of temporary migration as a function of climatic variables while controlling for potential sociodemographic and contextual confounders. Low-lying, densely populated, and agricultural, Bangladesh is broadly considered to be one of the places where climate change will first devastatingly impact livelihoods and migration. Thus, the Bangladesh context can provide us with early evidence of patterns we may observe in other similarly socio-environmentally situated countries over the next hundred years. In our research, we find that environmental variability plays a disruptive, rather than displacing, role in temporary migration, further complicating attempts to view this process through the lens of "environmental refugees". We show that migration decreases with riverine flooding in the short-term, while migration increases with temperature and decreases with extreme precipitation in the medium-term. These findings suggest a livelihoods-centered mechanism wherein long-established household income strategies (both temporary migration and agriculture) are disrupted by climatic variability.

2. Analyzing environmentally-induced temporary migration

In the growing literature on climate vulnerability and environmentally-induced migration, Bangladesh is widely considered to be ground zero for these processes (IOM, 2010). In this region, population exposure to environmentally-related disasters is indeed very high and has well-documented negative effects on various dimensions of population well-being (Banerjee, 2007; Del Ninno, 2001; Khandker, 2007; Valerie Mueller & Quisumbing, 2011). Probing beneath the surface of these claims, however, the evidence for widespread environmentally-induced migration in Bangladesh is actually rather thin. Several qualitative and small-scale studies have witnessed mobility related to flooding or coastal storms, but in most cases the vast majority of moves were short-term and temporary (Findlay & Geddes, 2011; Kartiki, 2011; Mallick et al., 2017; Mallick & Vogt, 2014; B. K. Paul, 2005; S. K. Paul & Routray, 2010; Penning-Rowsell, Sultana, & Thompson, 2013; Rahman, Paul, Curtis, & Schmidlin, 2015). A small number of demographic and econometric studies have also attempted to evaluate these claims, but, as described below, the majority of these studies suffer from significant methodological limitations.

Among these studies, Gray and Mueller (2012b) used longitudinal data over a 15-year period from 1,680 households in 102 communities to examine the impacts of aggregate self-reported shocks on long-term migration while controlling for spatial and social confounders. This analysis revealed positive effects of crop failure on migration and few effects of flooding, but this analysis did not incorporate biophysical measures of environmental shocks or address temporary migration. Joarder and Miller (2013) used data from a cross-sectional survey of 1,770 households in 26 villages to investigate the effects of household shocks on environmental migration, but this study was significantly limited by the small number of study sites, the absence of longitudinal data, and a reliance on self-classification of both shocks and environmental migration. Iqbal and Roy (2015) used district-level data on climate, agricultural production and net migration to show that climate-linked increases in production had a weak positive effect on net migration, but was limited by the use of indirect methods to estimate net migration (Iqbal & Roy, 2015). Most recently, Lu and colleagues (2016) used a large dataset of call records from mobile phones to examine population mobility associated with Cyclone Mahasen. Their analysis successfully documented short-term mobility in the hours before the storm, but was not able to document longer-term changes (Lu et al., 2016).

These studies illustrate both the opportunities and challenges of using large-sample data sources to directly measure environmental effects on migration. Our goal is to use a novel data source to answer basic empirical questions about environment and migration in rural Bangladesh: Does envrionmental variability displace migrants, and who is most vulnerable to these processes? To do this we draw on high-frequency demographic surveillance data on 200,000 individuals over an 18-year period, which combines the high frequency of call records (e.g., Lu et al., 2016) with the longitudinality of panel surveys (e.g., Gray and Mueller, 2012b). In addressing these questions, we also contribute to the larger literature on envrionmentally-induced migration, which has given relatively little attention to temporary migration or high-frequency data sources.

3. The Bangladesh Context

Bangladesh is located on a low-lying deltaic floodplain and climatically governed by the southeast monsoon weather regime. Over a fifth of the land of Bangladesh is flooded for approximately half the year, and sometimes as much as two-thirds of the land becomes uninhabitable during years when riverine flooding is an extreme weather event rather than a seasonal fluctuation (Mirza, 2002). As a result of the highly variable environment, the country is generally recognized as exceptionally vulnerable to climate change (Yu, 2010). Further exacerbating the gravity of these concerns is the high dependence of the population on rural livelihood strategies. The rural population comprised over two-thirds of the total population of Bangladesh as of 2014 (UNDESA, 2014). The agricultural sector provides employment for over 60% of the rural labor force and is the primary livelihood strategy of many households (Melorose, Perroy, & Careas, 2006). Traditionally, three types of rice (Aus, Aman, and Boro) and wheat have been the three most cultivated food crops in rural Bangladesh. Rainfall variability and extreme temperatures have been found to harm crop performance for these staple crops (Ruhul Amin, Zhang, & Yang, 2015). Likewise, in years of excessive flooding, many crops are destroyed and planting of new crops is delayed by water lingering on fields. The timing and extent of environmental events such as flooding and drought can therefore have a massive impact on the overall economy, as well as the food security and general well-being of Bangladeshi (Mirza, 2002).

However, the relationship between agriculture and livelihoods is changing. Bangladesh is a rapidly developing and urbanizing country. Between the years of 1970 and 2010, the proportion of the population living in a city increased from 7.6% to 30.5% (UNDESA, 2014). Similarly, the proportion of the GDP coming from agriculture declined from 32% in 1981 to 25% in 2000 (Shahabuddin & Quasem, 2002). Through migration, urbanization, infrastructural growth, and globalization, a growing number of people work outside the agricultural sphere. Many of these people are still members of agricultural households, though, reflecting an increase in livelihood opportunities and, subsequently, household livelihood diversification (Toufique & Turton, 2016).

Across Bangladesh, migration and mobility have become an integral part of rural livelihood strategies. In some cases, this means commuting daily for work; in others, migrants are away for days or years, seasonally or permanently relocating. Cyclical temporary migration is a common livelihood strategy for rural Bangladeshi households who must cope with agricultural and environmental variability (Afsar, 2003). Remittances provided by household members who have temporarily migrated to the city can help temper the impact of unstable crop prices and high interest rates on rice bought on credit during hunger season.

The study location, Matlab, is located in south-central Bangladesh, near the confluence of the Padma and Meghna rivers and has a long history of as a migrant-sending region (Figure 1) (Emch et al., 2008). Matlab is positioned near the primary highway, about six hours away (by boat or bus) from the two largest cities in Bangladesh, Dhaka and Chittagong. The relative proximity of Matlab to these urban centers is conducive to cyclical, temporary migration, wherein individuals migrate for seasonal work but return to Matlab for important events and to provide the household with support during cropping seasons (Kuhn, 2010). In Matlab in 1996, households with migrants received almost 30% of their total household income from remittances (Kuhn, 2010). While it is clear that migration plays an important role in the livelihood strategies of those in Matlab, it is unclear from this evidence to what extent migration decisions are a result of distress (including environmental shocks) or as a form of investment for a household. Our analysis addresses this fundamental question.

4. Data Sources

4.1 Sociodemographic

Migration data were collected through the Matlab Demographic Surveillance System (MDSS). Run by the International Centre for Diarrhoeal Disease Research, Bangladesh (ICDDR,B) since 1966, the MDSS is the longest running demographic surveillance system in the world. The total sample population of the study area in 2003 was about 200,000 individuals. From 1986 to 2003, the period during which our data were collected, survey enumerators conducted structured interviews with all of the households in the 142 study villages on a monthly basis.

Alongside the MDSS, ICDDR, B conducted detailed censuses of the socioeconomic characteristics of this population in 1982, 1996, and 2005. Data collected at these times include measures of household asset ownership, housing structural characteristics and size, access to water and sanitation, and amount of land owned by the household (ICDDR, 2014). These records can be linked to the surveillance data to generate household variables for each decade of data collection.

4.2 Environmental

Riverine flooding, temperature, and precipitation data used as predictors of migration were extracted from the Dartmouth Flood Observatory database and the NASA Prediction of Worldwide Energy Resource (POWER) database. The Dartmouth Flood Observatory is a global active archive of large flood events. Rather than using models or originating from a single data source, this database combines information from news, governmental institutions, water measurement instruments, and remote sensing sources to generate a comprehensive flood event database (Brakenridge, 2014). POWER data are generated from the Goddard Earth Observing System assimilation model (NASA, 2015). Additional biophysical controls were generated using the spatial locations of study households and a vector layer of the Dhonagoda River, which bisects the study MDSS study area.

5. Combining rich sociodemographic and environmental data

5.1 Migration

To analyze the impact of environmental events on migration, the data described above are used to create a person-month dataset including both migrants and non-migrants (Table 1). All individuals residing in the study area are considered to be at risk of migrating in a given month. As we are considering the potential of environmentally-induced displacement, we did not restrict our study population to people between the ages of 15 and 45, as is typical in labor migration research. Temporary migration is defined as an absence from the MDSS study area by any individual for more than one month, followed by a return to the study area by 2003. This definition excludes absences of only a few days, and, given that mortality and destination data were not available to this analysis, ensures that deceased individuals are excluded. With these parameters, 25,330 individuals (7% of the study population over the time period) participated in a migration event at some point over the 18 years. Though the person-month rate of migration is low, there are a very large number of total migration events over the period—54,770 discrete events. Of those who migrated, 82.6% engaged in no more than two temporary migrations, with the median length of a migration spell being roughly two years.

5.2 Environmental Factors

To produce our dichotomous measure of riverine flooding, flood data from the Dartmouth Flood Observatory were added to a spatial database of the study area. If areas of flooding overlapped with any part of the study area during a given month, the study area was marked as flooded. We used this approach because the DFO does not measure flood locations at a high spatial resolution and the study area is at a consistent, low-lying elevation. Over the study period, 17% of months contained a flood. There were 15 separate flood events, lasting on average for 2.5 months at a time. To further confirm the validity of using these flooding data, we compared z-score standardized measures from the closest Bangladesh Water Development Board non-tidal river gauge (Station 114) to our flooding indicator from the Dartmouth Flood Observatory (Figure 2). Though the river gauge is only available for 99 months of 216-month study period, Figure 2 illustrates that our flood measure matches very closely with deviations from the normal river level.

Once we extracted the daily precipitation and temperature measures for the Matlab study site from the POWER database, we averaged them by month to generate mean temperature and precipitation. Monthly rainfall ranged from 0 to 540 mm, with an average rainfall of 138 mm. The average monthly temperature was 27 C, with a range from 20 to 34 C. Neither precipitation nor temperature has shown a marked change over the 216 months of the study period, though average precipitation appears to have increased slightly while average temperature appears to have marginally decreased.

5.3 Controls

We also control for sociodemographic factors typically associated with migration including household wealth, age, gender, and household size (Bilsborrow, McDevitt, Kossoudji, & Fuller, 1987; Ellis, 2000; Massey, Axinn, & Ghimire, 2010; Massey & Espinosa, 2014). To generate our measure of household wealth, we used polychoric principal components analysis on household asset data from the Matlab Socioeconomic Censuses (Angeles, 2009; Filmer & Scott, 2012). Assets used to create the index included ownership of bicycles, watches, radios, cows, boats, hurricane lamps, and the material out of which the walls and roof of the primary house are made. Our analysis indicated that over 50% of the variance was explained by the first principal component, and so we used this to represent household wealth. The raw values of the first principal component were rescaled to range from 0 to 10. Age in years during month *t*, gender, and household size were derived from MDSS.

Biophysical controls include distance to the river and flood protection. Areas closer to the river are more susceptible to flood damage from river overflow, while households within the protected zone (described below) are less likely to suffer extensive property damage from heavy flooding in the study area. To produce the control for distance to river, we used ArcGIS to measure the distance from each bari (household cluster) to the nearest point on the Dhonagoda River, which bisects the study area. Likewise, we controlled for whether the bari was located in the flood protection zone of the Meghna-Dhongoda Irrigation Project (MDIP) in month *t*. The MDIP involved building a large earthen embankment along the northern boundary of the Dhonagoda, along with culverts, bridges, and pumping stations (Ansary et al., 1997). The MDIP is one of several embankments and other water control measures put in place through the Bangladesh Flood Action Plan. About half of the Matlab study area is currently protected from river overflow by the MDIP (Emch, 2000). The purpose of the MDIP, and other water control measures throughout Bangladesh, is to protect crops from flood damage and river erosion, as well as to reduce the communication and infrastructure damage caused by seasonal riverine flooding (Ansary et al., 1997). Prior to 1989, the embankment was not operational and the flood protection by embankment control is therefore time-varying.

5.4 Modeling Migration

Using these data, we employ discrete time survival models to estimate the impact of environmental variables (flooding, precipitation, and temperature) on migration. This approach is appropriate for the person-month structure of the data and accounts for censoring due to migration. For each of the models described below, we estimate the following equation:

$$log\left(\frac{\pi_{it}}{1-\pi_{it}}\right)=\beta X_{it},$$

where π_{it} is the odds of migration for individual i in month t, X_{it} is a vector of independent variables for individual i in month t, and β is a vector of parameters for the effects of the Independent variables. Independent variables include measures of environmental exposure as well as controls for month of year, age, sex, household size, distance from river, household asset value, whether or not the household is protected from flooding, and month in the sequence to adjust for background trends in migration. Models are also clustered on month in sequence to account for the scale of measurement of the environmental variables and the non-independence of migration decisions occurring in the same temporal context. In addition to modeling migration at the month of exposure, we use moving averages to generate lagged terms to examine the impacts of environmental events from the previous 12 or 24 months on migration. We model this relationship with (Table 3) and without (Table 2) sociodemographic times environment interaction terms, and we use predicted probabilities to present outcomes from these models (Figures 2–4).

6. A complex story

Table 2 contains the results of our primary model, which indicates that in rural Bangladesh, flooding, precipitation, and temperature have jointly significant but variable short and medium-term impacts on temporary migration decisions. The results of the primary model are discussed first, followed by the results of the interacted models.

At the month of occurrence, flooding has a significant negative impact on short-term migration decisions. Individuals have 17% lower odds of migrating in a month of flooding than in a month without flooding (Odds ratio: 0.83, $p<0.05$). This finding is in opposition with the current discourse on “environmental refugees”, which suggests that extreme weather events (increased by climate change) may spur mass migration for this population (IOM, 2010; Myers, 2002). Beyond the month of occurrence, flooding does not affect migration. Over the medium term (12 and 24 month moving averages), though not the short term, precipitation has a significant nonlinear impact on migration (Figure 3). Drought and excess rainfall both decrease the predicted probability of migration. Farmers plant for average rainfall, and crop varieties have been bred to thrive under typical (optimal) growing conditions. Therefore, crops are likely to be stunted by drought or drowned by excess rainfall, decreasing agricultural yield and crop productivity (Ruhul Amin et al., 2015). Decreased household crop income likely contributes to the decrease in migration after a period of non-optimal rainfall. Increases in temperature over a two-year time period are revealed to increase migration (Figure 4). Increased temperatures have been shown to have a strongly negative impact on agricultural income through crop stunting and withering (Mueller et al., 2014; Ruhul Amin et al., 2015). Further, non-farm income also appears to be impacted by temperature extremes (Mueller et al., 2014). The long-term cumulative loss of income may provide a push factor for migration.

Examining the interactions, the strongest relationship is one of gender differentiated migration patterns for precipitation and temperature (Table 3). Men are significantly more likely to migrate than women especially when rainfall is normal to low, suggesting that high rainfall might increase demands for farm labor (Figure 4). Unlike precipitation, an increase in temperature increases men’s probability of migration while simultaneously decreasing women’s probability of migration. The divergence of this effect may be caused by differing gender roles in Bangladesh. Men may be pushed to migrate for economic opportunity after facing crop failure and loss of agricultural and non-farm income, as mentioned before, while women may lose their opportunity to migrate for marriage or education with a decrease in available agricultural income (Mueller et al., 2014). These gendered effects highlight the constraints to adaptation frequently experienced by women across the developing world, who may be limited by access to resources, societal norms, and household responsibilities (Fordham, 2003).

In addition to gendered migration patterns, we also observe that wealthier households are more likely than poorer households to send migrants during drought months and less likely to send migrants during months with above average rainfall. This finding suggests that wealthy households have more adaptive flexibility when responding to drought, and are not as likely to be pushed into involuntary migration due to extreme rainfall (Luers, 2005).

Those who are protected from rising waters by the embankment have a higher probability of migrating with below average rainfall and a lower probability of migrating with above average rainfall. Households protected by the embankment are different from those not protected in that they do not experience the same degree of crop loss as a result of riverine flooding during monsoons. Therefore, these households are more likely to have the resources to allow migration for adaptation in times of drought, as in the case of wealthier households, and are not as likely to be forced to migrate by heavy rainfall events that may lead to flooding. The wealth and embankment protection interaction effects underscore, and provide additional evidence for, the considerable barriers to migration as an adaptation strategy for those households who lack sufficient livelihood stability and financial resources (Adger, 2006). In regard to month in the sequence, we observe that migration is increasingly linked to precipitation over time. Households experiencing above average amounts of rain at the end of the time period are much more likely to send migrants, while heavy rainfall events have almost no impact on migration at the beginning of the study period. As described previously, migration is increasingly used as a household adaptation strategy in Bangladesh, and households experiencing above average rain are well positioned to send migrants.

Neither the household size nor the distance to the river interactions had a significant impact on the environment-migration relationship (Table 3). However, the effects of the controls were generally significant and in line with theoretical expectations (Alam & Barkat-e-Khuda, 2011; Kuhn, 2010). Men were more likely to migrate than women, individuals between ages 15 and 35 were most likely to migrate, and wealth increased migration. Protection from the damaging effects of floods increased migration, likely because these households were less likely to suffer a regular loss of assets and had increased livelihood stability. Household size actually decreased migration, possibly because larger households lacked the necessary assets to send migrants.

7. Conclusions

Building upon the increasingly rich environmental migration literature, we analyze the impact of precipitation, temperature, and riverine flooding on temporary migration in non-coastal rural Bangladesh over almost two decades. We use discrete time event history models to improve our understanding of whether environment displaces migrants and how sociodemographic characteristics impact vulnerability to migration. In sum, we find that riverine flooding has an instantaneous negative impact on migration while medium-term increases in precipitation have a nonlinear impact on migration and temperature has a positive impact on migration, illustrating the complexity of the relationship between environmental factors and migration. The results from our analysis have significance for the substantive literatures on these topics as well as for research methods and policy.

From a theoretical perspective, our findings demonstrate the complex, time-dependent, and nonlinear relationships between environmental variability and temporary migration. These results highlight the importance of questioning the current discourse on environmentally driven displacement. Consistent with previous research on long-term migration (Gray and Mueller, 2012a; Mueller et al., 2014), the results suggest that climate changes are more likely to impact migration decisions over the medium to long term through a livelihoods pathway rather than directly, through an environmental shock such as flooding. While we find that both above and below average rainfall decreases medium-term migration, likely by decreasing agricultural productivity, we do observe that increased temperature increases probability of migration over time. This finding adds to previous research that has found mixed effects of precipitation but generally positive effects of temperature on human migration (Bohra-mishra et al., 2014; Gray and Wise, 2016; Mueller et al., 2014; Nawrotzki and Bakhtsiyarava, 2016), and suggests that, in a warming world, gradually increasing temporary migration in this context is a likely outcome. Our results also challenge current narratives about vulnerability to environmentally induced migration (McLeman & Hunter, 2010): We find that temporary migration flows are mediated by gender and wealth, but do *not* find that vulnerable populations such as women and the poor are consistently more likely to be displaced under environmental extremes.

The results also have important implications for the literatures on environmental adaptation and on contemporary labor migration. In a rural and agrarian region of Bangladesh that is highly exposed to environmental change, we show that households are highly responsive to environmental variability and use temporary migration to cope with these changes. However, multiple barriers to this form of adaption exist: Low-asset households are less able to send migrants during droughts, and households lacking flood protection are more often pushed to send migrants during floods. These results suggest that policy interventions such as cash transfer programs and expansions of flood protection could give households more options to respond to future environmental shocks associated with climate change. Regarding contemporary labor migration, our results contribute to a literature documenting that migration is costly and that even temporary moves can be undermined by a lack of resources (Bryan et al., 2014; Dustmann & Okatenko 2014), in this case by short-term flooding and by medium-term wet and dry precipitation shocks. Given this context, policies that buffer against shocks (e.g., crop insurance) or reduce barriers to migration (e.g., land registration) should be considered in order to improve access to livelihood-enhancing temporary migration.

Methodologically, we combine remotely sensed environmental data with demographic surveillance system data to develop an analytic approach that can be used to examine temporary migration at a very fine temporal scale. Using these monthly data allows us to avoid the issues inherent in using retrospective migration histories and perceptions of past environmental shocks. We are also able to analyze temporary migration patterns, which are generally neglected due to data limitations. Finally, we are able to examine migration patterns multiple years out from a environmental event, due to our 18 years of monthly data and the longitudinal nature of demographic surveillance data. Given the increasingly availability of remotely-sensed environmental data (Brakenridge et al., 2013) and demographic surveillance data (Sankoh & Byass, 2012) our results suggest additional opportunities down this path.

In conclusion, our research has implications in the broader discussion of displacement in the face of global climate change. Globally, and especially in Bangladesh, climate change is expected to increase environmental events such as riverine flooding, increase heat stress through temperature rise, increase variability and amount of precipitation, and induce sea level rise (IPCC, 2014). Our research suggests that climate change is much more likely to disrupt current livelihoods-oriented migration flows than to directly induce mass displacement, at least for non-coastal Bangladesh. Further, rather than being displaced by climate shocks, it is possible that individuals may find themselves trapped due to a loss of resources to migrate (Black et al., 2011). Though policymakers may not be able to prevent households from experiencing the negative effects of climate change, our findings suggest that programs to increase household in situ resilience would go a long way to decoupling the relationship between migration, household well-being and agriculture.

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Highlights

- Riverine flooding does not have a long-term impact on temporary migration.
- Optimal precipitation and above average temperatures have sustained positive effects on temporary migration.
- Households in Matlab, Bangladesh draw on a range of strategies to cope with environmental variability.

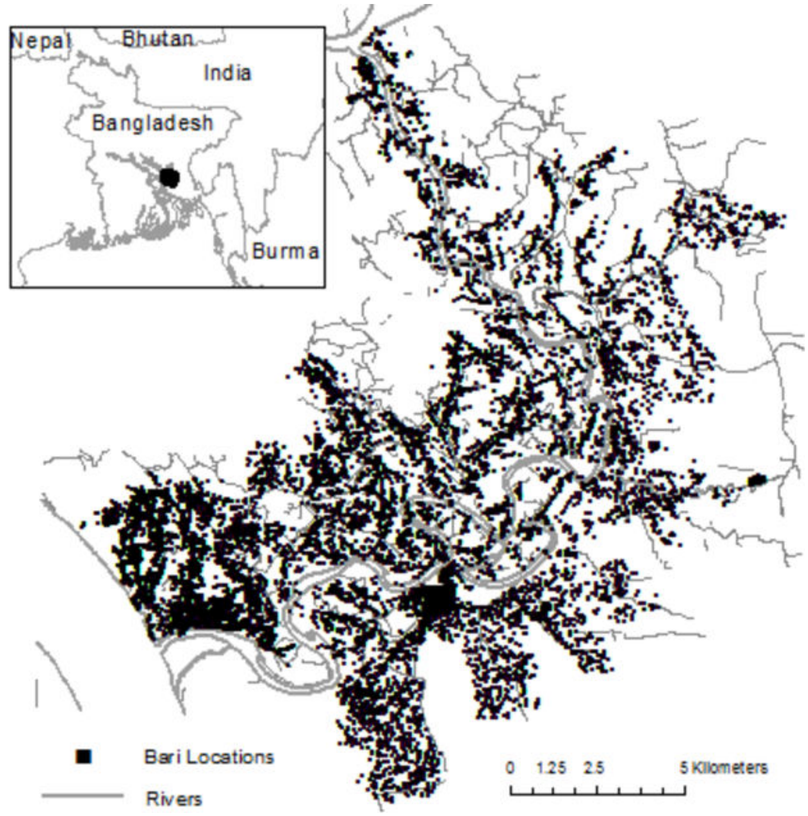

Figure 1.
Map of the study area showing location of baris

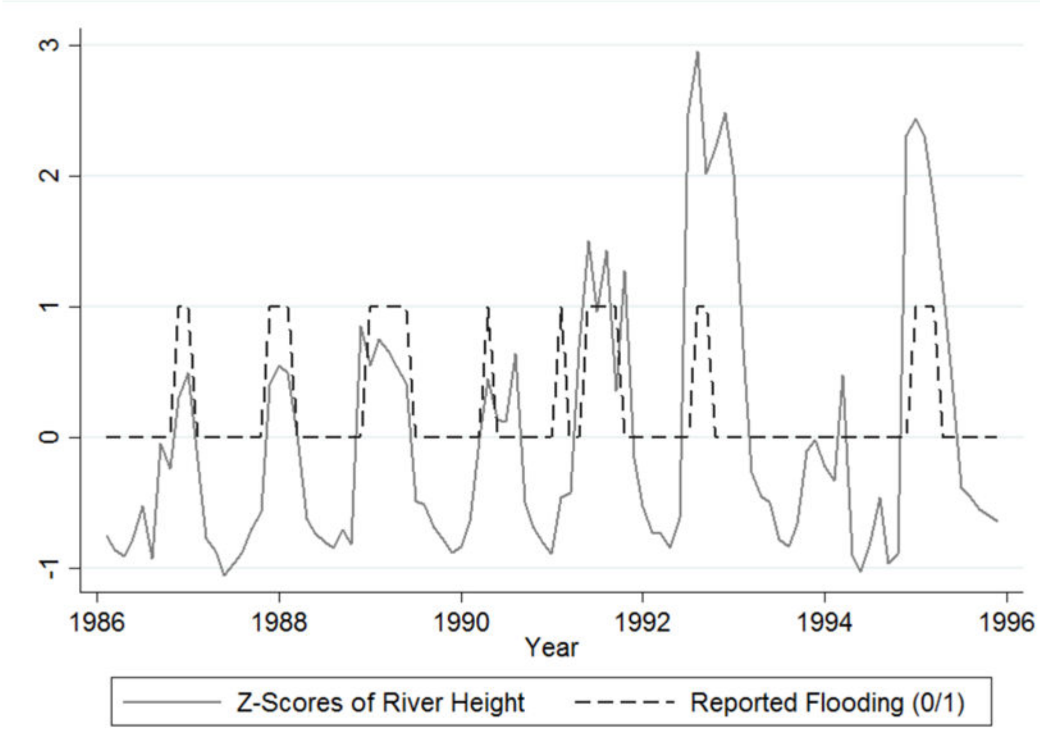

Figure 2.

Comparison of gauge-measured river height with the flood measure used in the analysis (99 months, 1986–1995).

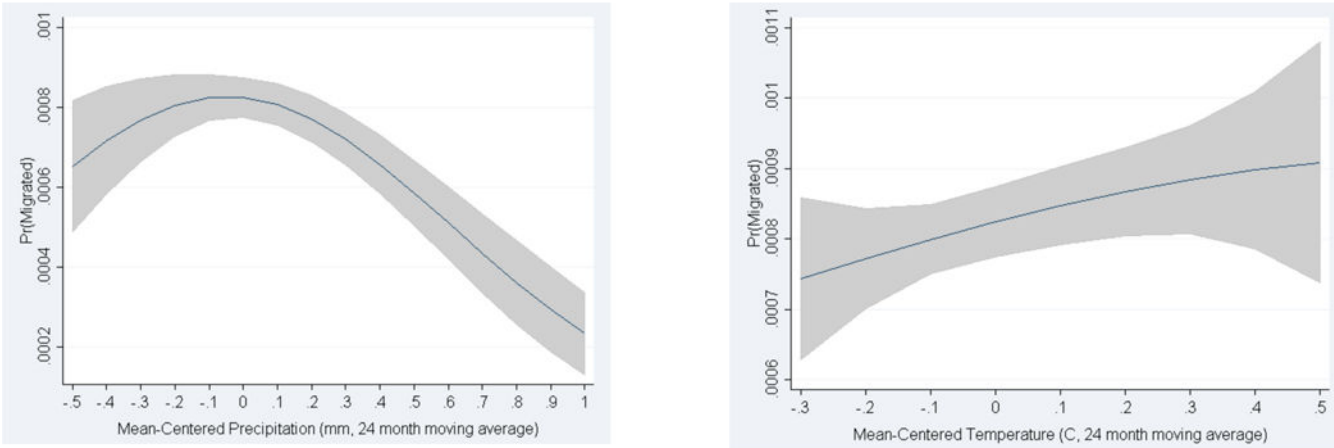

Figure 3.
Predicted probabilities of migration as a function of precipitation and temperature.

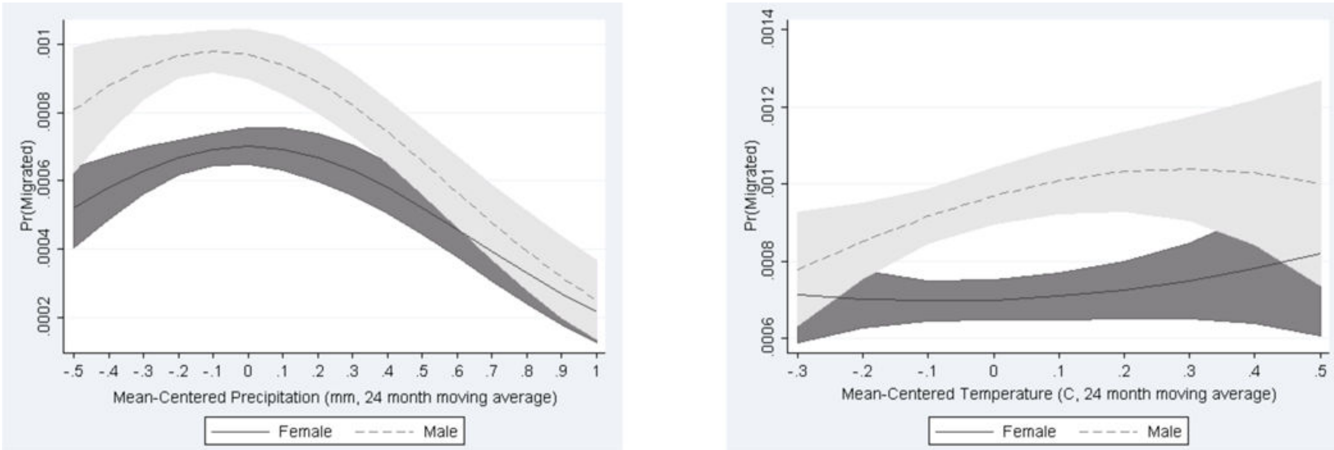

Figure 4.
Predicted probabilities of migration for men and women as a function of precipitation and temperature

Table 1

Definitions and person-year values for all variables

Variable	Unit	Level	Source	Mean	Min	Max	Definition
Outcome							
Migration	0/1	Person-month	Matlab DSS	0.001	0	1	Migrated in month indicated by 1, presence in study area indicated by 0
Predictors							
Environmental Predictors							
Flooding							
1 month	0/1	Month	Dartmouth Flood Observatory	0.17	0	1	Flood in month indicated by 1
12 months	0/1	Month	Dartmouth Flood Observatory	0.15	0.00	0.42	Moving average of flooding over last 12 months
24 months	0/1	Month	Dartmouth Flood Observatory	0.15	0.00	0.33	Moving average of flooding over last 24 months
Precipitation							
1 month	mm/day	Month	NASA POWER	0.00	−4.64	12.79	Mean-centered mean daily precipitation in month
12 months	mm/day	Month	NASA POWER	0.00	−1.25	1.09	Moving average of mean-centered daily precipitation over last 12 months
24 months	mm/day	Month	NASA POWER	0.00	−0.66	0.96	Moving average of mean-centered daily precipitation over last 24 months
Temperature							
1 month	C	Month	NASA POWER	0.00	−6.84	7.08	Mean-centered mean temperature in month
12 months	C	Month	NASA POWER	0.00	−0.50	0.90	Moving average of mean-centered temperature over last 12 months
24 months	C	Month	NASA POWER	0.00	−0.31	0.53	Moving average of mean-centered temperature over last 24 months
Individual Controls							
Male	0/1	Person	Matlab DSS	0.48	0.00	1.00	Gender is male, reference category is female
Age	#	Person-year	Matlab DSS	25	0	99	Age in years
Household Controls							
Flooding Protection	0/1	Bari-month	GIS	0.27	0	1	Protection from flooding by embankment
Wealth Index	0–10	Household-year	Matlab Socioeconomic Census	4.32	0	10	Index of household asset ownership
Household Size	#	Household-month	Matlab DSS	5.87	1	38	Number of individuals in household
Distance from River	meters	Bari	GIS	962.4	0.239	4073	Distance from bari to Dhonagoda River
Temporal Controls							
Month in Sequence	month	Month	Matlab DSS	130.2	1	216	Month in dataset (1 through 216)
Month of Year	month	Month	Matlab DSS	6.565	1	12	Month of year, included as one indicator per month

Table 2

Coefficients from the event history analysis of migration

	Month of environmental event	12 month environmental lag	24 month environmental lag
Environmental Predictors			
Flooding	−0.187 *	0.044	0.891
Flooding^2	N/A	−0.432	0.413
Precipitation	−0.004	−0.291 **	−0.108
Precipitation^2	−0.002	−0.462 ***	−1.155 ***
Temperature	−0.038	0.012	0.292 *
Temperature^2	0.009	0.118	−0.218
Individual Controls			
Male	0.260 ***	0.261 ***	0.261 ***
Age [a]			
0–4	−0.949 ***	−0.953 ***	−0.954 ***
5–9	−1.536 ***	−1.545 ***	−1.546 ***
10–14	−1.502 ***	−1.511 ***	−1.514 ***
15–19	−0.435 ***	−0.435 ***	−0.435 ***
25–29	−0.253 ***	−0.254 ***	−0.255 ***
30–34	−0.788 ***	−0.794 ***	−0.795 ***
35–39	−1.290 ***	−1.299 ***	−1.301 ***
40–44	−1.667 ***	−1.669 ***	−1.670 ***
45–49	−2.125 ***	−2.124 ***	−2.127 ***
50–54	−2.266 ***	−2.270 ***	−2.271 ***
55–59	−2.585 ***	−2.590 ***	−2.594 ***
60–64	−2.390 ***	−2.398 ***	−2.398 ***
65–69	−2.262 ***	−2.268 ***	−2.272 ***
70–74	−2.120 ***	−2.124 ***	−2.124 ***
75+	−1.821 ***	−1.819 ***	−1.821 ***
Household Controls			
Flooding Protection	0.156 ***	0.146 ***	0.145 ***
Wealth Index	0.029 ***	0.027 ***	0.027 ***
Household Size	−0.068 ***	−0.067 ***	−0.067 ***
Distance from River	0.000 **	0.000 **	0.000 **
Temporal Controls			
Month of Year [b]			
February	−0.140	−0.559 ***	−0.557 ***
March	−0.025	−0.592 ***	−0.594 ***

	Month of environmental event	12 month environmental lag	24 month environmental lag
April	−0.180	−0.677***	−0.664***
May	−0.121	−0.714***	−0.699***
June	0.206	−0.523***	−0.506***
July	0.225	−0.576***	−0.535***
August	0.085	−0.634***	−0.593***
September	−0.141	−0.777***	−0.737***
October	−0.224	−0.772***	−0.770***
November	−0.681**	−1.054***	−1.056***
December	−0.824**	−0.869**	−0.862**
Month in Sequence	−0.004***	−0.002	−0.001
Constant	−5.380***	−4.915***	−5.186†
Joint Test of Environmental Predictors	9.390†	42.270***	57.500***
Joint Test of Flooding	N/A	0.040	2.210
Joint Test of Precipitation	1.760	37.750***	33.54***
Joint Test of Temperature	2.260	0.940	6.040*

†p < .10;

*p < .05;

**p < .01;

***p < .001

N= 27,320,910 person-months

[a]Reference category: 20–24,

[b]Reference category: January

Table 3

Coefficients from the event history analysis of 24 month envrionmental predictors interacted with household characteristics

	Interacted Controls					
	Gender	Wealth Index	Household Size	Distance from River	Flooding Protection	Month in Sequence
Environmental Predictors						
Flooding	0.054	−0.833	0.101	0.934	1.450	−2.563
Flooding x Flooding	3.421	3.946	2.673	0.328	−0.642	1.925
Precipitation	0.001	0.173	−0.189	−0.158	−0.061	1.295 *
Precipitation x Precipitation	−1.183 ***	−0.965 **	−1.302 ***	−1.200 ***	−1.088 ***	2.345 **
Temperature	0.084	0.189	0.273	0.193	0.328 *	0.123
Temperature x Temperature	0.467	1.224	−0.090	0.370	−0.520	−0.040
Interactions						
Flood x	1.608 *	0.383	0.142	0.000	−1.904	0.007
Flood x Flood x	−5.747 **	−0.779	−0.409	0.000	4.407	0.057
Precipitation x	−0.209 **	−0.063 **	0.014	0.000	−0.193 †	−0.007 †
Precipitation x Precipitation x	0.037	−0.043	0.025	0.000	−0.188	−0.018 ***
Temperature x	0.397 **	0.025	0.003	0.000	−0.075	0.001
Temperature x Temperature x	−1.298 **	−0.339 †	−0.023	−0.001 *	2.521 †	0.003
Individual Controls						
Male	0.214 ***	0.262 ***	0.261 ***	0.261 ***	0.261 ***	0.262 ***
Age[a]						
0–4	−0.954 ***	−0.956 ***	−0.953 ***	−0.954 ***	−0.954 ***	−0.956 ***
5–9	−1.547 ***	−1.549 ***	−1.546 ***	−1.547 ***	−1.546 ***	−1.550 ***
10–14	−1.515 ***	−1.516 ***	−1.514 ***	−1.514 ***	−1.514 ***	−1.515 ***
15–19	−0.436 ***	−0.435 ***	−0.435 ***	−0.436 ***	−0.435 ***	−0.435 ***
25–29	−0.254 ***	−0.256 ***	−0.255 ***	−0.255 ***	−0.255 ***	−0.256 ***
30–34	−0.796 ***	−0.796 ***	−0.795 ***	−0.795 ***	−0.795 ***	−0.798 ***
35–39	−1.302 ***	−1.303 ***	−1.301 ***	−1.301 ***	−1.301 ***	−1.304 ***

	Interacted Controls					
	Gender	**Wealth Index**	**Household Size**	**Distance from River**	**Flooding Protection**	**Month in Sequence**
40–44	−1.670***	−1.672***	−1.670***	−1.670***	−1.670***	−1.670***
45–49	−2.125***	−2.128***	−2.126***	−2.127***	−2.127***	−2.128***
50–54	−2.270***	−2.271***	−2.271***	−2.271***	−2.271***	−2.273***
55–59	−2.595***	−2.596***	−2.594***	−2.595***	−2.595***	−2.596***
60–64	−2.400***	−2.401***	−2.397***	−2.399***	−2.398***	−2.400***
65–69	−2.272***	−2.275***	−2.271***	−2.272***	−2.272***	−2.273***
70–74	−2.124***	−2.127***	−2.123***	−2.124***	−2.124***	−2.123***
75+	−1.819***	−1.823***	−1.819***	−1.822***	−1.820***	−1.818***
Household Controls						
Flooding Protection	0.145***	0.145***	0.145***	0.146***	0.244**	0.137***
Wealth Index	0.027***	0.002	0.027***	0.026***	0.026***	0.024**
Household Size	−0.067***	−0.067***	−0.076***	−0.067***	−0.067***	−0.067***
Distance from River	0.000**	0.000**	0.000**	0.000	0.000**	0.000*
Temporal Controls						
Month of Year[b]						
February	−0.557***	−0.557***	−0.557***	−0.557***	−0.554***	−0.551***
March	−0.594***	−0.596***	−0.594***	−0.594***	−0.590***	−0.581***
April	−0.665***	−0.669***	−0.665***	−0.665***	−0.670***	−0.680***
May	−0.699***	−0.700***	−0.699***	−0.699***	−0.700***	−0.663***
June	−0.506***	−0.505***	−0.506***	−0.506***	−0.509***	−0.481***
July	−0.535***	−0.534***	−0.535***	−0.535***	−0.536***	−0.493***
August	−0.593***	−0.592***	−0.593***	−0.593***	−0.594***	−0.599***
September	−0.737***	−0.735***	−0.737***	−0.737***	−0.738***	−0.779***
October	−0.771***	−0.769***	−0.770***	−0.770***	−0.771***	−0.795***
November	−1.056***	−1.054***	−1.056***	−1.056***	−1.055***	−1.081***
December	−0.862**	−0.859**	−0.862**	−0.862**	−0.861**	−0.891**

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	Interacted Controls					
	Gender	Wealth Index	Household Size	Distance from River	Flooding Protection	Month in Sequence
Month in Sequence	−0.001	−0.001	−0.001	−0.001	−0.001	−0.004
Constant	−5.163***	−5.076***	−5.134***	−5.208***	−5.225***	−4.584***
Joint Test of Environment and Interactions	140.130***	86.360***	60.950***	69.960***	84.530***	96.640***
Joint Test of Interactions	87.030***	27.260***	4.690	6.800	28.670***	31.460***
Joint Test of Flooding and Interactions	22.660***	8.360*	4.700	2.230	7.960*	3.240
Joint Test of Precipitation and Interactions	38.800***	43.530***	41.610***	35.130***	45.550**	57.520***
Joint Test of Temperature and Interactions	15.000**	11.870*	7.040	12.180**	11.030**	7.610

† p < .10;

* p < .05;

** p < .01;

*** p < .001

N= 27,320,910 person-months

[a] Reference category: 20–24

[b] Reference category: January