LETTERS
PUBLISHED ONLINE: 26 JANUARY 2014 | DOI: 10.1038/NCLIMATE2103

nature climate change

Heat stress increases long-term human migration in rural Pakistan

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Human migration attributable to climate events has recently received significant attention from the academic and policy communities[1,2]. Quantitative evidence on the relationship between individual, permanent migration and natural disasters is limited[3–9]. A 21-year longitudinal survey conducted in rural Pakistan (1991–2012) provides a unique opportunity to understand the relationship between weather and long-term migration. We link individual-level information from this survey to satellite-derived measures of climate variability and control for potential confounders using a multivariate approach. We find that flooding—a climate shock associated with large relief efforts—has modest to insignificant impacts on migration. Heat stress, however—which has attracted relatively little relief—consistently increases the long-term migration of men, driven by a negative effect on farm and non-farm income. Addressing weather-related displacement will require policies that both enhance resilience to climate shocks and lower barriers to welfare-enhancing population movements.

Donors spend approximately 4.6 billion dollars per year in emergency relief for natural disasters[1]. Astonishing forecasts of the number of environmentally displaced persons are broadly based on measures of population exposure and ignore individual adaptation[2]. Recent quantitative evidence suggests that individual, permanent migration increases with natural disasters and climate shocks, but not uniformly[3–9]. Empirical work on the causes of migration has typically been limited to analysis of data covering only a few years, and can therefore conclude little about migration in the longer term. Using a unique, 21-year longitudinal survey (1991–2012), we examine the long-term migration of household members in response to states of extreme temperature and rainfall in rural Pakistan. Significantly expanding on previous studies of climate-induced migration, we allow climate effects to be time-varying, multidimensional, interactive, nonlinear, and heterogeneous, all while accounting for various spatial and temporal confounders. This approach reveals a complex migratory response that is not fully consistent with common narratives of climate-induced migration.

Pakistan is highly vulnerable to climate change and involuntary displacement. In 2010 alone, floods in Pakistan affected 20 million people, destroying an estimated crop value of 1 billion US dollars[10]. Some 14 million people relocated temporarily, and 200,000 moved to internal displacement camps funded by international donors[11]. Uncharacteristically high temperatures (heat stress) also reduce population well-being by lowering agricultural yields. For example, the early maturity of wheat grains as a result of heat stress reduced Pakistani wheat yields by 13 per cent in 2010[12]. However, Pakistan's social protection programs and international relief efforts have been far more responsive to flood victims than heat stress victims, as in other parts of the developing world.

This study aims to answer three unresolved questions in this literature. First, which weather patterns explain the long-term mobility patterns of men and women in Pakistan? Second, is there evidence that extreme rainfall and heat affect agricultural income—indicating a possible channel through which they impact migration? The channels through which disasters affect migration have rarely been addressed owing to data limitations[13]. Third, are there barriers to weather-induced movement? Knowledge of what motivates migration and the barriers to adaptation through migration is important for designing appropriate policies that respond to natural disasters, migration, and displacement.

To answer all of these questions, we construct a longitudinal survey based on the Pakistan Panel Survey (PPS) collected in 1986–1991 (ref. 14) and two tracking studies (Supplementary Methods). The heads of the 1991 PPS households or proxy respondents were resurveyed in 2001 and 2012 to track the movement of original, 1991 household members. The data collected from the PPS and the two tracking studies are used to build an individual-level panel of migrating and non-migrating household members over a 21-year period. We create a person-year dataset following previous work[5,6,15–18]. As migration rates are very low for individuals younger than 15 or older than 39, individuals are included in the dataset, starting from baseline or when they reach age 15, and excluded after migrating or when they turn 40. This sample consists of 44,791 person-years, where 4,428 individuals are represented from 583 households.

To answer the first question, we employ discrete-time event history models to measure individual responsiveness to weather variables, controlling for baseline (1991) household wealth and demographic characteristics, and for village and time fixed effects. (Explanatory variables are summarized in Supplementary Table 1.) We estimate the event history model as a logit model, analysing migration as a binary dependent variable. A household member is considered a migrant in year t if he was permanently not present in year t for reasons other than death. The individual is considered a within-village migrant if they moved elsewhere in the village, and an out-of-village migrant if they moved outside of the village (including abroad). The multinomial event history model, estimated as a multinomial logit, differentiates the impacts of weather anomalies on local (within-village) versus long-distance (out-of-village) moves, and gender-differentiated migration[5,6]: $\log(\pi_{rit}/\pi_{sit}) = \alpha_{rt} + \alpha_{rv} + \beta_r X_{it}$, where π_{rit} is the odds of moving distance r for individual i in year t, π_{sit} is the odds of not moving, and parameters α_{rt} and α_{rv} are the baseline hazard of mobility in village v and year t, respectively, for the specific types of mobility r.

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Table 1 | Migration responses to climate.

	Men						Women					
	Logit move		Multinomial logit distance of move				Logit move		Multinomial logit distance of move			
			In village		Out of village				In village		Out of village	
Specification A												
Rainfall	1.28		0.94		1.93	**	1.19		1.24		1.17	
Temperature	2.69	***	2.42	***	2.90	**	1.87	***	2.03	**	1.69	*
Joint test of variables	17.92	***			21.96	***	11.60	***	13.92	***		
Specification B												
Rainfall	1.05		1.75		0.53		1.04		1.59		0.62	
Temperature	2.62	***	2.64		2.42	**	1.85	***	2.06	**	1.53	
Rainfall × Temperature	1.01		0.97		1.07	*	1.01		0.99		1.03	*
Joint test of variables	17.92	***			26.32	***	14.56	***	21.80	***		
Specification C												
Rainfall in Q1	1.47		1.51		1.57		1.13		0.99		1.36	
Rainfall in Q4	0.82		0.84		0.81		1.20		1.20		1.30	
Temperature Q1	0.84		1.02		0.68		0.83		0.80		0.84	
Temperature Q4	5.09	***	2.83	***	11.16	***	1.85	***	1.82	***	2.19	**
Joint test of variables	25.53	***	41.83	***			15.45	***	21.87	***		
Specification D												
Flood	0.96	*	0.96	*	0.96		0.97	**	0.95	***	0.99	
Temperature	3.00	***	2.76	***	3.35	***	2.00	***	2.22	***	1.74	*
Joint test of variables	18.98	***			22.45		13.11	***	17.01	***		
Specification E												
Moisture index	0.71	*	0.70		0.75		0.75	**	0.64	**	0.85	
Individuals	2,125		2,147				2,303		2,303			

Q abbreviates quartile; the omitted category in nonlinear models is the interquartile range. All coefficients reflect odds ratios. Inverse probability weights account for individual attrition. Standard errors are clustered at the village level. Statistical significance of parameters based on *t* tests, where ***, **, and * indicate $p < 0.01$, $p < 0.05$, $p < 0.10$. Joint tests of statistical significance based on Chi-squared tests. Source: Pakistan Panel Survey 1991; Pakistan Panel Tracking Surveys 2001, 2012.

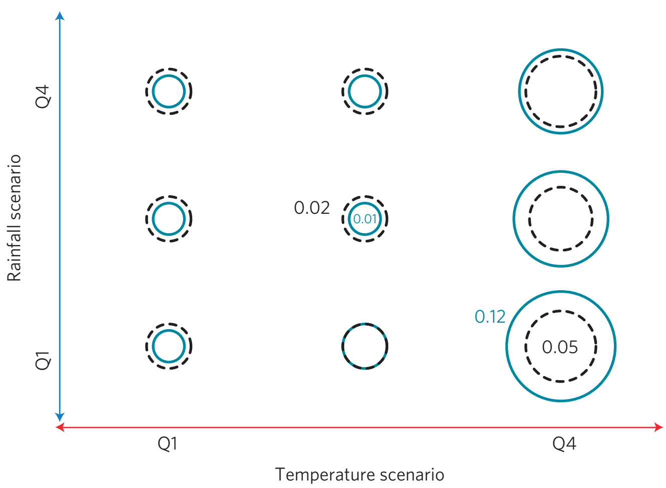

Figure 1 | Predicted probabilities of out-of-village migration by gender. The bubble size reflects the predicted probabilities obtained using Specification C under different temperature and rainfall extreme scenarios (Supplementary Table 5). Solid teal green bubbles indicate the probability of men moving out of the village in a given scenario. Black dashed bubbles indicate the probabilities of women moving out of the village in a given scenario. Predicted probabilities are specified for the scenario where the temperature and rainfall lie in the interquartile range and extreme hot scenario (low rainfall, high temperature) for reference.

X and β_r vectors of controls and their corresponding parameters estimates. Inverse probability weights are used to correct estimates for individual attrition (Methods).

From various secondary data sources (Supplementary Methods), we construct the key weather variables included in the analysis: cumulative rainfall over the monsoon period (June–September), average temperature over the Rabi season (November–April) when wheat is grown, a measure of flood intensity (the annual number of deaths caused by flooding)[19], and a 12-month moisture index—the Standardized Precipitation Evapotranspiration Index[20] (SPEI). All weather variables are measured at the village level, with the exception of flood intensity, which varies by province. Our preferred specifications use average weather values from year t and $t-1$ to capture the weather preceding period t migration decisions. Trends seem stationary and migration corresponds with peaks in temperature (Supplementary Fig. 1).

Table 1 presents results of migration responses to weather by gender using an event history model, and further by within-village and out-of-village moves using a multinomial event history model. We focus on the estimates of the weather parameters (though estimates of all coefficients are presented in Supplementary Table 2). Specifications A–C present results from linear and nonlinear specifications of the rainfall and temperature variables (Methods).

Overall, we observe no robust effect of rainfall on the mobility of men or women. Men are slightly more likely to move out of the village in response to greater rainfall levels, but only when temperature is also sufficiently high (Specification B). When

Table 2 | Marginal effects of rainfall and temperature extremes on annual income, with 90% confidence intervals.

	Net farm income	90% confidence interval	Farm wage income	90% confidence interval	Non-farm income	90% confidence interval
Variable mean (1000s of Rupees)	44.15		0.75		31.45	
Rainfall in Q1	−9.25	[−20, 1]	−0.12	[−0.5, 0.3]	3.93	[0.4,7.5]
Rainfall in Q4	13.92	[2, 26]	1.31	[0.4, 2]	15.38	[10, 20]
Temperature Q1	−10.20	[−28, 8]	0.32	[−0.0, 0.6]	−4.70	[−9,−0.2]
Temperature Q4	−15.89	[−31, −0.6]	0.59	[−0.1, 1]	−4.90	[−10, −0.1]
Households	648					

The marginal effects are computed using the point estimates from a linear regression which includes household and time fixed effects. Confidence intervals are based on village-clustered standard errors. Incomes given by Rupee value in the year 2000. Source: Pakistan Panel Survey (1986–1991).

Table 3 | Migration responses to rainfall and temperature extremes by land ownership and asset wealth.

	Owned land				Asset wealth			
	None distance of move		Some distance of move		First tercil distance of move		Third tercile distance of move	
	In village	Out of village	In village	Out of village	In village	Out of village	In village	Out of village
Rainfall in Q1	1.40	1.07	1.09	1.70 *	1.41	1.11	1.04	1.56
Rainfall in Q4	1.41	1.37	0.89	0.91	1.23	1.45	0.83	0.75
Temperature Q1	0.97	1.01	0.74	0.65	0.67 *	0.90	1.81 **	0.81
Temperature Q4	1.69	4.89 ***	2.55 ***	2.67 **	2.66 ***	2.98 **	1.41	2.31 *
Joint test of variables	13.26		40.30 ***		28.28 ***		14.77 *	
Individuals	1,592		2,858		2,204		2,246	

All coefficients reflect odds ratios. Inverse probability weights used in all models. Statistical significance parameters based on *t* tests, where ***, **, and * indicate $p < 0.01$, $p < 0.05$, $p < 0.10$. Joint tests of statistical significance based on Chi-squared tests. Source: Pakistan Panel Survey 1991; Pakistan Panel Tracking Surveys 2001, 2012.

we flexibly allow rainfall and temperature to have a nonlinear impact on migration by including dummy variables for rainfall and temperature in the first (Q1) and fourth (Q4) quartiles (the omitted groups being the second and third quartiles), we find that it is only temperature in Q4 that significantly affects migration. Specification D, (controlling for flood intensity instead of rainfall), further corroborates that flooding has no effect on out-of-village moves and indeed causes a modest decline in the within-village migration of men and women.

However, the results consistently show that men move out of the village in response to extreme temperatures in the Rabi season (Specifications A–D). Last, when the weather variables are substituted by a moisture index (Specification E), we see that periods of high moisture in general are associated with the retention (as opposed to migration) of household members. Thus, we are left with an overall picture that heat stress—not high rainfall, flooding, or moisture—is most strongly associated with migration. The risk of a male, non-migrant moving out of the village is 11 times more likely when exposed to temperature values in the fourth quartile (Specification C). Male migration responses are robust to accounting for spatial autocorrelation (Methods).

Figure 1 provides the predicted rates of out-of-village migration for both men and women, based on the preferred model (Specification C, which flexibly allows for nonlinear effects). Men and women consistently migrate the most under scenarios with extreme temperature. The baseline migration of men (women) moves from 0.01 (0.02) to 0.12 (0.05) under the scenario of temperature in Q4 (extreme heat) and rainfall in Q1 (extreme scarcity).

Is there evidence that extreme rainfall and heat affect agricultural income—indicating a possible channel through which they impact migration? To answer this second question, we examine how fluctuations in temperature have affected the annual farm, farm wage, and non-farm income of the PPS households during 1986–1991. We estimate a linear regression including rainfall and temperature extreme variables (as in Specification C), along with household and time fixed effects. Table 2 shows the marginal effects of temperature and rainfall on various sources of income, with 90% confidence intervals. Agricultural income suffers tremendously when temperatures are extremely hot (in Q4)—wiping out over a third of farming income. Non-farm income also experiences losses from heat stress, but to a lesser extent (16%). Interestingly, high rainfall increases all sources of income substantially. This analysis suggests one possible reason why heat stress drives migration, whereas extreme rainfall does not: heat stress (unlike rainfall) provides a negative income shock.

Are there barriers to weather-induced movement? To answer this final question, we examine the relationship between mobility and weather anomalies by land ownership and asset wealth to see whether financial constraints influence migration decisions (Table 3). Interestingly, extreme heat stress is associated with more migration for both land-owners and non-land owners, and for those in the first and third terciles of asset wealth. However, the magnitude and statistical significance of the estimates are most pronounced for the land- and asset-poor, and their moves are most likely to be out-of-village moves. It seems that for the poor, the migration benefits following heat stress outweigh the moving costs, spurring migration of all forms. The poor may have more locational flexibility as they are not tied to land or assets which can be hard to sell, and at risk of loss if untended. Furthermore, given that the poor often provide goods and services to land cultivators, this is consistent with our finding in Table 2, where we showed that heat stress especially reduces rural non-farm income. When farmers are hit by a shock, the livelihoods of those dependent on providing goods and services to them will also be affected.

Our empirical work offers the first quantitative evidence of how long-term migration decisions in Pakistan are affected by weather extremes. Both women and men respond to heat stress by moving, but men mostly move long distances. Our results are consistent with earlier evidence of risk diversification through the marriage migration of women in India[21]. Long-distance moves also coincide with farm income losses, yet men seem more responsive to temperature fluctuations and historically are inclined to migrate for employment in this setting. Although all individuals use migration to cope with heat stress, the poor are more likely than the rich to relocate outside of the village.

Our study has broader policy relevance for development strategy in Pakistan. Existing flood relief programs may potentially crowd out private coping mechanisms such as migration, particularly for the poor and risk-averse living in flood-prone areas. Our results also show the important role of heat stress—a climate shock which has attracted relatively less relief—in lowering farm and non-farm income and spurring migration. Sustainable development will require policies that enhance adaptation to weather-related risks for farmers and for enterprises tied to the rural economy. Shifting relief towards investments in heat-resistant varieties, producing and disseminating better weather forecasting data and weather insurance, and policies that encourage welfare-enhancing migratory responses might improve individual abilities to adapt to an array of weather-related risks[22,23].

Methods

To account for individual attrition, all of our statistical models use inverse probability weights constructed from the ratio of predicted probabilities, of remaining in the sample between 1991 and 2012, from a restricted and unrestricted probit model (Supplementary Table 4)[24,25]. The F statistic testing the joint significance of the rainfall variable and its interaction with temperature ($p < 0.05$) suggests Specification B is preferred to Specification A for the sample of men under the multinomial logit model. Conclusions are similar when including five-year (rather than one-year) fixed effects (Supplementary Table 5) and without averaging values from year t and $t-1$ (Supplementary Table 6); the latter being imprecise owing to the collinearity between weather variables. We test for the robustness of the results of Specification C under spatial correlation[26] using a grouped bootstrap (where years are resampled and replaced) for the logit model (Supplementary Table 7). Male migration responses remain responsive when facing temperature in the fourth quartile.

Received 26 September 2013; accepted 16 December 2013; published online 26 January 2014

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Acknowledgements

The authors are grateful for assistance and constructive comments from M. Auffhammer, M. Call, P. Dorosh, S. Hamza Haider, S. Hausladen, L. Hunter, J. Koo, H. L. Lee, S. Malik, J-F. Maystadt, H. Nazli, C. Ringler, W. Schlenker, E. Schmidt, T. Thomas, H. Tilahun, H. Xie, T. Zhu, and Innovative Development Strategies in this research. The participation of C.G. was supported by the National Institutes of Health (R00HD061752).

Author contributions

V.M., C.G. and K.K. designed and performed the research, analysed the data, and wrote the paper.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to V.M.

Competing financial interests

The authors declare no competing financial interests.