When the well runs dry, where do we go now? Exploring internal migration due to climate stress in Asia and Central and South America

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1. Background

The recent series of record-breaking weather events around the world follow a long-term trend of increasing heat waves, heavy precipitation, droughts and wildfires. As the Intergovernmental Panel on Climate Change (IPCC) warned, a warmer future climate is likely to exacerbate both the frequency and intensity of extreme weather events (e.g., floods, heat waves and tropical storms) and graduate processes of environmental degradation (e.g., losses of cropland and biodiversity, land degradation, desertification and soil erosion) (IPCC, 2007). These climate change effects pose serious threats to food security, health and water availability. The increase in livelihood insecurity can in turn trigger human migration as a coping strategy to adverse consequences of climate change.

The possibility of climate change inducing major migratory and refugee movements has gained sizeable attention among policy makers and researchers. In particular, climate change is expected to hit less developed countries harder than advanced industrialized countries due to their often vulnerable location vis-à-vis climate events, high population densities, weak structure of government and infrastructure, and lower adaptive capacity (IPCC, 2014). Hence there are increasing concerns across UN agencies, think tanks and NGOs (Boas, 2015) regarding the insecurity caused by climate change. These are reflected in a number of predominantly non-scientific reports outlining the potential humanitarian crises due to environmentally induced migration (Castles, 2002; Christian Aid, 2007; Lee, 2001; McGregor, 1993).

Despite an increase in scholarly and policy interests regarding the impacts of climate change on migration, knowledge in the field remains varied, patchy and limited (Piguet et al., 2011). For

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instance, estimates and predictions of climate/environmental migrants are in fact rooted only in one or two publications, especially those of Norman Myers, a British environmentalist. Using a crude method, Myers (2002, 1993) calculated the number of people likely to be affected by sealevel rise and an increase in extreme weather events in vulnerable regions based on anticipated population growth in the coming decades and predicted between 150 to 200 million environmental migrants in 2050. However, in the absence of relevant statistical information, it is not possible to assess such predictions. In fact, given the current scientific knowledge of environmental migrants seems to be implausible, let alone predictions (Gemenne, 2011).

These limitations are the result of complex linkages between environmental change and migration. Migration influenced by environmental change is normally operated through a range of other drivers including social, political, economic and demographic factors (Black et al., 2011; Fussell et al., 2014). Environmental change can directly lead to migration or the climate impacts on migration are indirectly mediated through economic and political factors which are affected by environmental change. While extant studies on environment-migration connections provide rich empirical insight into migration decision-making process, sociodemographic characteristics of migrants, type of migration, types of environmental change influencing migration such as in Adamo and Izazola, 2010; Fussell et al., 2014; Hunter et al., 2015; Obokata et al., 2014. These studies are often based on specific geographic areas or limited to one country. Indeed, Fussell et al. (2014) highlighted the importance of using comparable migration data to better understand the connections between environmental change and migration across a broad range of countries and types of environmental change and migration across a broad range of countries and types of environmental change and migration across a broad range of countries and types of environmental change and migration across a broad range of countries and types of environmental change and migration across a broad range of countries and types of environmental events.

To this end, this study aims to model internal migration flows of 26 countries in Central and South America and Asia and examine the influence of origin and destination (push and pull) factors, including environmental stress, in driving migration. Using micro census data, the paper focuses on modelling migration flows at the aggregate level to obtain a broader outline of the issues at hand. To our knowledge, such aggregate cross-national analysis has only been carried out in sub-Saharan Africa (Garcia et al., 2015). This study hence provides new empirical evidence of climate-related migration flows in other developing world countries.

We focus on internal migration rather than international migration because most climate-driven migration are often short distance, within national borders and much of it is directed from rural to urban area (Gill, 2010; McLeman, 2013; McLeman and Hunter, 2010). In fact most migration, regardless of drivers, involves movements within national boundaries and often yield far larger numbers than those across international boundaries. Likewise, in studies that compare both internal and international migration, the number of climate-related internal migrants is typically found to be higher than the number of international migrants (Dun, 2011; Findley, 1994; Gray, 2009).

2. Data

2.1 Migration and sociodemographic data

Migration and socioeconomic data are derived from harmonized census microdata samples from the Integrated Public Use Microdata Series (IPUMS) International database (Minnesota Population Center, 2014). Each set of census microdata contains a small random sample (0.4%-10%) of unidentified private households and associated persons based on a full census conducted by the national statistical agency in each country. Table 1 presents the list of countries used in this study which contains 77 samples from 26 countries – 11 from Asia and 15 from Central and South America – drawn from censuses collected between 1970 and 2011. Countries used in the study were selected based on their location in Central and South America or Asia with available information on migration. Figure 1 illustrates a map of countries used in this study.

[TABLE 1 AND FIGURE 1: ABOUT HERE]

One advantage of using the IPUMS database is that the explanatory variables are harmonized and standardized to allow for cross-country comparisons. However, the geographical detail available for each country is not uniform and depends on the density of the sample size, the distribution of the population and how administrative units are defined for each country. Furthermore, even within the same country, subnational geographical boundaries are not consistent over time. Although working with greater geographical detail allows us to capture distance between place of origin and destination more precisely, for comparison purpose across countries and census years, we aggregated the geographical units to be at the first administrative level (i.e. province, department or state level).

2.2 Geographic boundary data

Information on geographical boundaries of each administrative unit is required in order to calculate distance between origin and destination as well as identifying contiguous regions. Geographical boundaries are also used to match micro census data with climate data. Administrative unit boundary files for each country are obtained from the Global Administrative Areas Database (GADM) (Global Administrative Areas, 2015).

2.3 Climate data

Precipitation data are obtained from the CRU-TS historic climate database version 3.22 produced by the Climate Research Unit at the University of East Anglia (University of East Anglia Climatic Research Unit et al., 2014). The time-series data for rainfall consist of monthly mean precipitation spanning from the period 1901 to 2013 calculated on high-resolution (0.5 x 0.5 degree) grids. The precipitation grids are used to calculate drought and rainfall variability for each administrative unit.

3. Measurement and model specification

As a preliminary exercise, the analysis is built upon the methods and measurement employed by Garcia et al. (2015) for sub-Saharan Africa.

3.1 Measurement

Count of **migration flows** (y_{ij}) are taken from the question which asks individuals where they lived previously. The migration question is asked differently in each country using a different temporal resolution either 1) place of residence five years ago; or 2) length of stay in current location and place of previous residence. For the latter where the continuous temporal period of migration is available, we extracted one- and five-year migration flows.

Distance $(DIST_{ij})$ between origin and destination is computed using Euclidean distance i.e. straight-line distance between two points calculated from the center of the source cell to the center of each of the surrounding cells. **Contiguity** $(CONT_{ij})$ is a dummy variable equals 1 if regions are continuous, 0 otherwise.

We also consider other demographic and socioeconomic variables previously found to be associated with migration based on the information in the census microdata for each administrative unit. There variables include: 1) total number of population (*POP*); 2) proportion living in an urban environment (*URBAN*); 3) proportion economically active (*ACTIVE*); 4) proportion male (*MALE*); and 5) median age (*AGE*).

Drought (*DROUGHT*) variable refers to the number of droughts in the 25-year period before the census. Drought is identified when an annual rainfall is 10% below the annual mean rainfall for the 25-year period before the census. **Rainfall variability** (*RAINVAR*) is calculated based on the number of months in the past rainy seasons with rainfall 50% lower than the mean rainfall for the corresponding month during the 25-year period before the census.

3.2 Model specification

A sequence of spatial interaction models are fit using Poisson regression for each country, time and migration interval combination. Derived from the gravity theory of migration (Zipf, 1946), this model focuses on the role of distance in explaining spatial movements as well as population sizes. In an extension of the spatial interaction model, other relevant factors such as unemployment rates or GDP can also be considered jointly (Lowry, 1966; Morrison, 1973). For the analysis of migration flows, a set of variables are sequentially added, starting with Zipf (1946) specification for count of internal migrant transitions (y_{ij}) between origin *i* and destination *j*. Environmental variables are added at the end in order to observe the impact of environmental driver on migration controlling for other relevant drivers.

The models estimated can be written as:

$$\begin{aligned} y_{ij} \sim Poisson (\lambda_{ij}) \\ \lambda_{ij} &= \beta_0 + \beta_1^0 log POP_i + \beta_1^D log POP_j + \beta_2 DIST_{ij} \\ &+ \beta_3 CONT_{ij} \\ &+ \beta_4^0 URBAN_i + \beta_4^D URBAN_j \\ &+ \beta_5^0 ACTIVE_i + \beta_5^D ACTIVE_j \\ &+ \beta_6^0 MALE_i + \beta_6^D MALE_j \\ &+ \beta_7^0 AGE_i + \beta_7^D AGE_j \\ &+ \beta_8^0 DROUGHT_i + \beta_8^D DROUGHT_j \\ &+ \beta_9^0 RAINVAR_i + \beta_9^D RAINVAR_j \end{aligned}$$

4. Results [TABLE 2: ABOUT HERE]

A summary statistics of parameters used in the spatial interaction models is presented in Table 2. The average population size per administrative unit in our Asian sample is slightly higher than that of Central and South America sample. The proportion of urban population is only 33% in Asia as compared to 65% in Central and South America. On the other hand, the proportion employed is 72% in the former and 55% in the latter. It appears that drought events and low rain fall episodes are more frequent

[FIGURE 2: ABOUT HERE]

Figure 1 presents the parameter estimates of migration flows from in the final model where all parameters are included. Since a Poisson model assumes the logarithm of its expected value, negative value represents lower migration flows while positive value refers to higher migration flows. The standard gravity variables i.e. the population size and distance appear in an expected direction. Migration flows are greater in origin and destination areas with higher number of population. Distance is considered to be a proxy of the migration costs hence migration flows are greater, the shorter the distance between origin and destination. Contiguity parameter further captures the spatial interaction structure showing that controlling for distance, migration is even higher between adjacent administrative units.

We also detected a pattern of rural-to-urban migration particularly in Central and South America where migration is greater in the destination with higher proportion of urban population. Similarly, migration flows also increase with the proportion of male population in the destination. It seems that migration is higher the greater the proportion of actively employed

population both in the origin and destination areas. This is contrast of what expected that unemployment rates in the origin would push people to migrate to the areas with better employment prospect. This finding might be due to relatively high labour market participation in these regions, especially in informal sector. Meanwhile, median age appears to have no relationship with migration flows.

Pertaining to the climate-related factor, controlling for socioeconomic drivers we find that migration flows are greater in the origin area experiencing higher frequencies of droughts. There is however no clear patter with respect to the relationship between rainfall variability and migration.

5. Discussion

Modelling internal migration flows across 26 Central and South American and Asian countries covering the period 1970-2011, we do find that climate driver as measured by drought influences outmigration from areas frequently affected by droughts. Likewise, where people migrated from and to also depend on demographic and socioeconomic characteristics of the origin and destination. This kind of analysis offers aggregate measure of spatial and environmental determinants of migration flows.

This analysis is however a preliminary exercise that we firstly aim to replicate the earlier work by Garcia (2015) in sub-Saharan Africa. In the next steps, we plan to explore different modelling methods such as multilevel model which allows us to fit the parameters for all countries at the same time or negative binomial regression which deals with over dispersion. In addition, climate data and measurement of climatic shocks/extreme events will be improved. Drought index will be calculated for more immediate period before the migration year rather than the 25-year span. Other climate-related data such as temperature, soil moisture, and Agriculture Stress Index (ASI) will be introduced. The ASI which is useful to detect severity of agriculture drought, for instance, might be more relevant for the rural areas where livelihoods mainly rely on farming. Finally, we will redefine and further explore other push-pull factors. We will further include share of households engaged in agriculture in the analysis and also plan to employ better measurement of urban area and economic activity.

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Country	Year						
Asia:							
Cambodia	1998	2008					
China	1990						
India	1983	1987	1999				
Indonesia	1971	1976	1980	1985	1990		
Iraq	1997						
Krygyzstan	1999						
Malaysia	1991	2000					
Mongolia	2000						
Philippines	1990	2000					
Thailand	1970	1980	1990	2000			
Vietnam	1989	1999	2009				
Central and South America:							
Argentina	1970	1980	1991	2001			
Bolivia	1976	1992	2001				
Brazil	1970	1980	1991	2000	2010		
Chile	1970	1982	1992	2002			
Colombia	1985	1993	2005				
Costa Rica	1973	1984	2000				
Cuba	2002						
Dominican Republic	1981	2002	2010				
Ecuador	1974	1990	2001	2010			
El Salvador	1992	2007					
Mexico	1990	1995	2000	2005	2010		
Nicaragua	1971	1995	2005				

Table 1: List of countries used in this study and corresponding census years.

Peru	2007				
Uruguay	1975	1985	1996	2006	2011
Venezuela	1981	2001			

Notes: Year highlighted in bold represent the census where one- and five-year migration flows are available. Year listed in a normal font represent five-year migration flows.

Variable	Ν	Mean	Std. Dev.	Min	Max		
Asia							
Population	1005	108236	340181.4	75	5324172		
Distance	15166	5.73	5	0.18	43.11		
Contiguity	15166	0.09	0.28	0	1		
Proportion urban	898	0.33	0.21	0	1		
Proportion male	1005	0.5	0.02	0.46	0.61		
Median age	1005	21.76	4.11	15	37		
Proportion employed	877	0.72	0.14	0.31	0.95		
Drought index	986	5.87	2.41	0	12		
Rainfall variability	480	20.92	22.5	0	125		
Central and South America							
Population	993	121934.9	213878.9	273	2018950		
Distance	7208	6.19	6.07	0.09	33.94		
Contiguity	7208	0.18	0.38	0	1		
Proportion urban	752	0.65	0.19	0.11	1		
Proportion male	993	0.5	0.02	0.45	0.67		
Median age	993	22.3	4.69	14	38		
Proportion employed	866	0.55	0.07	0.32	0.81		
Drought index	987	7.7	2.56	0	20		
Rainfall variability	833	32.21	34.61	0	171		

Table 2: Summary statistics of parameters used in the spatial interaction models

Figure 1: Map of countries used in this study







Area 🔶 Asia 🔶 Latin America

Figure 2: Parameter estimates of internal migration flows using Poisson regression