

## **PAA Abstract Submission: The Social Consequences of Environmental Migration in Africa**

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An emerging literature empirically establishes that individuals migrate to adapt to climate variability (Gray and Mueller, 2012; Bohra-Mishra et al., 2014; Mueller et al., 2014; Thiede et al., 2016). How these adaptation strategies affect society is poorly understood (Brzoska and Frohlich, 2016; Burrows and Kinney, 2016). The common pathways in which environmental migration is meant to affect society are through ethnic tensions between migrants and residents in receiving areas, competition for low-skilled jobs and resources, and overall perceptions of migrants bringing insecurity (Burrows and Kinney, 2016).

We propose to provide one of the most comprehensive empirical analyses measuring the social consequences of environmental migration on natives in receiving communities in Africa. To our knowledge, there have only been three peer-reviewed studies that quantify the consequences of environmental migration in developing countries, with a focus on employment outcomes (Strobl and Valfort, 2015; Maystadt, Mueller, and Sebastian, 2016; Kleemans and Magruder, 2018). Only one of the three studies is based on data from an African country (Strobl and Valfort, 2015). We posit the influx of environmental migrants at the destinations may affect society in that their presence may place pressure on labor markets, resources and services; create ethnic tensions; and foster ill-perceptions of migrants. It remains an additional open question whether any of the above relationships may contribute to societal unrest in receiving areas.

Recent efforts to make censuses available online (e.g. IPUMS International) and the availability of numerous geospatial datasets have made testing the aforementioned hypotheses more feasible. Data collected from satellites has allowed researchers to monitor poverty changes at destinations through night lights activity (Henderson, Storeygard, and Weil, 2012; Jean et al., 2016), and any coinciding modifications in vegetation due to urban expansion (DeFries et al., 2010). A related literature has used these data sources to highlight why the competition for resources might be important in the context of the displacement of conflict refugees (Alix-Garcia, Bartlett, and Saah, 2013; Müller et al., 2016). In our case, the impacts on vegetation will largely depend on the proportion of environmental migrants relative to the population, whether environmental migrants congregate in a few destinations, and the destinations of choice. One might expect that environmental migrants will be attracted to distinct location choice sets than those seeking refugee camps.

The paucity of work in this arena is largely attributable to the difficult task of providing a reliable estimate of the effect of environmental migration on the outcomes of natives residing in host economies. First, there is the question of how one distinguishes environmental immigration from broader economic migration (Fussell, Hunter, and Gray, 2014; Kondylis and Mueller, 2014). Second, estimating a causal relationship between the outcome of interest and environmental immigration is quite challenging (Kondylis and Mueller, 2014). Endogeneity issues arise from the fact that environmental migrants may be attracted to locations with better economic activity or environmental outcomes, which creates the potential for positively biased estimates on the effects of environmental migration (Boustan, Fishback, and Kantor, 2010). The endogeneity of migration has traditionally been addressed by using an instrumental variables approach, but as Maystadt, Mueller, and Sebastian (2016) note many of the instrumental variables that are commonly used to address the endogeneity issue are more susceptible to violating the exclusion restriction in this area of the world. To address these concerns, we adopt the procedure used by Maystadt, Mueller, and Sebastian (2016).

## Data

### *Migration*

Migration outcomes are constructed from individual-level data collected by IPUMS in 8 sub-Saharan African countries from 1976 to 2010 (Minnesota Population Center, 2015). Permanent migration is defined by a binary variable for whether the individual migrated out of the origin district in the last year. The sample includes approximately 27 million individual observations. For every country, we can predict which specific districts are particularly vulnerable to a rise in environmental immigration and measure its subsequent consequences.

### *Demographics and Employment*

All censuses collect information on the gender, age, completed education, and employment of the respondent. We use this information to quantify migration rates by the male/female, youth (15-34 years old)/adult (35+ years old), and skilled/unskilled subpopulations, with the intention to test differential responses to climatic shocks across subpopulations. We also use the information to gauge whether environmental migration hampers the employment prospects of men, youth, and the unskilled more than women, adults, and the skilled, respectively.

We focus on two sets of native employment outcomes based on the responses to individual employment status and worker classification questions. We first create three binary variables in which indicate whether the individual was self-employed, unemployed, or inactive. Conditional on being part of the employed sample, we create three additional binary variables which indicate whether the person is engaged in self-employed, wage/salary, or unpaid labor. Unknown and missing responses are possible answers to the employment and worker classification questions, but are not coded. We drop any individuals who are classified under these categories, after verifying that the percentage of individuals is negligible and non-random.

### *Climate*

We use high-resolution gridded data from the Climate Research Unit's (CRU) Time Series to create climate variables (Harris et al., 2014). CRU is a monthly global dataset at 0.5° resolution (~50 km at the equator) that is derived by interpolating data from a network of over 4000 stations, including a large number in Sub-Saharan Africa (UEACRU et al. 2015). CRU data are considered to provide reliable climate information in Africa (Zhang, Kornich, and Holmgren, 2013), and previous studies have shown CRU to be a significant predictor of internal migration in both Africa (Gray and Wise, 2016) and Latin America (Thiede, Gray and Mueller, 2016). We extract precipitation and temperature from this source as annual spatial means at the origin districts, and then transform these values into climate anomalies (z-scores) relative to a constant 1981-2010 reference period (Thiede, Gray and Mueller, 2016). These values capture the magnitude and direction of climate shocks relative to the local historical climate, and have been shown to be stronger predictor of internal migration in Africa than raw climate values (Gray and Wise, 2016).

### *Conflict*

To measure conflict, we use monthly gridded data on the number of conflict events, generated by O'Loughlin, Linke, and Witmer (2014) at 1 degree resolution (~100 km) for all of Sub-Saharan Africa and the period 1980-2012. These data were generated by replicating the methodology of the Armed Conflict Location and Event Dataset (ACLED) for the 1980-1996 period and aggregating this to ACLED

data from 1997-2012. The ACLED methodology involves systematically reviewing news and NGO reports of conflict and then coding the nature, location, participants and number of fatalities from each event, including battles, civilian killings, riots, protests and recruitment activities (Raleigh et al., 2010). The level of non-conflict-related media activity can be included as a control to account for potential reporting biases (O'Loughlin, Linke, and Witmer, 2014). Compared to the other commonly-used subnational conflict event database, the Uppsala Conflict Data Program Georeferenced Event Dataset (Sundberg and Melander, 2013), ACLED captures a much larger number and range of events and, with the extension by O'Loughlin, Linke, and Witmer(2014), also covers a much longer time period. We extract these data for our destination districts at an annual time scale for the analysis.

### *Vegetation*

The Enhanced Vegetation Index (EVI2) from NASA MEaSUREs Vegetation Index and Phenology global datasets are used to quantify changes in landscape. These datasets were created at 5.6 km resolution for the 1981-2014 period using surface reflectance from the AVHRR and MODIS satellites (Didan, 2016). EVI2 is a measure of vegetative growth, and has multiple advantages over NDVI (an older vegetation index) including lack of saturation in dense tropical vegetation (Zhang, 2015). We extract annual data on mean EVI2 at the destination district level, and then transform these values into z-scores as described above for climate. These vegetation z-scores capture deviations from historical vegetation conditions such as those caused by forest clearing, agricultural expansion and urban expansion.

### *Night Lights*

To measure urbanization and economic activity, we use nighttime lights imagery available from NOAA. Nighttime lights data are increasingly being used and validated as a high-resolution, time-varying measure of local economic activity, urbanization and population, particularly in contexts such as Sub-Saharan Africa where such data are scarce (Chen and Nordhaus, 2011; Henderson, Storeygard, and Deichmann, 2012; Donaldson and Storeygard, 2016). Data on nighttime lights at approximately 1 km resolution for the 1992-2013 period are available from the DMSP-OLS Nighttime Lights Time Series (NCEI, 2017). The cleaned data on “stable lights” are radiometrically corrected as described by Witmer and O'Loughlin (2011) to account for variation in sensor properties over time. These data are then extracted as annual means of the sum of light intensity in each study district. These district-level light values are then transformed into z-scores as described above to capture the change in nighttime light conditions over time.