Title: Climate Variability and Local Environmental Stressors Influencing Migration in Nang Rong, Thailand

Authors: Jacqueline Meijer-Irons, University of Washington
Benjamin Chabot-Hanowell, University of Washington
Matthew D. Dunbar, University of Washington
Sara R. Curran, University of Washington

ABSTRACT

Scholars point to climate change, often in the form of more frequent and severe drought, as a potential driver of migration in the developing world, particularly in populations that rely on agriculture for their livelihoods. To date, however, there have been few large-scale, longitudinal studies that explore the relationship between climate change and migration. This study significantly extends current scholarship by evaluating distinctive effects of slow onset climate change and short-term extreme events upon different migration outcomes. Our analysis models the effect of the environment--as measured by Normalized Difference Vegetation Index (NDVI) and the occurrence of El Nino Southern Oscillation (ENSO) events—on migration out of Nang Rong. Our preliminary findings indicate that predominantly dry El Niño periods of 24 months duration lead to outmigration, while predominantly wetter La Niña periods of 12-month duration reduce outmigration. Clustered monthly patterns of annual NDVI fluctuation indicate that villagers living in pixels that exhibit early, consistently higher, and steep rising green-up are less likely to migrate out in the subsequent year.

INTRODUCTION

Climate scientists predict that climate change will influence migration patterns of rural residents who rely on agriculture for their livelihoods (IPCC 2007). While there was some initial concern that climate change would lead to mass out-migration from rural areas into urban areas and across borders, attention has turned instead to the role of selective migration from rural to urban areas as an adaptation strategy for communities affected by climate change. In many cases, these moves are predicted to be internal moves, and may take the form of temporary, circular moves or permanent ones (Hugo et al. 2009). This migration might serve as a means of alleviating predicted challenges to traditional agricultural livelihoods, such as declines in harvest yields brought on by increased and prolonged periods of drought (Barnett and Weber 2010; Tacoli 2009; Adger et al. 2009; IPCC 2007). Out-migration as an adaptive strategy is already being employed in many regions of the world, where temporary and permanent migration is used as a way to buffer household exposure to risk, sending members of households to earn additional income that is later remitted back to the family of origin (de Haan 1999; Kniveton, Schmidt-Verkerk, Smith, and Black 2008; Stark and Taylor 1989; Tacoli 2009). It is difficult to highlight climatic change or environmental degradation as the main factor explaining migration flows, particularly when considering overlapping causes of migration that include economic, social and political factors (Castles 2002; Hugo 2008). Migration and environmental degradation are both complex processes that require multi-level analysis in order to understand how the two interact (Curran 2002). However, a body of conceptual and empirical work has emerged to help us understand the role of the environment in migration flows and to shape the debate about climate change and migration (Findley 1994; Henry, Schoumaker, and Beauchemin 2004; Gray 2009; Gray and Mueller 2011; Massey, Axinn, and Ghimire 2007, McLeman and Smit 2006). Our study contributes to this line of inquiry with a longitudinal analysis of global and local climate variability and its impact on out migration from rural, Northeastern Thailand over a 16-year period.

BACKGROUND

Previous work on migration and environment points towards much greater complexity in human responses to variability in climate and local environmental conditions. Rather than observing the emergence of large numbers of environmental refugees, it appears that climate variability, as opposed to climate change, and a wider array of migration responses, including variations in timing and distance, are key factors that must be taken into account to better assess the relationship. First, migration outcomes are not uniform. Several studies point to the importance of measuring and accounting for the temporal and spatial distinctions of migration, as well as the composition of the migrant streams. Second, the explanations for the much more variable patterns tend to hinge on interactions between the social and economic contexts and the environmental conditions that prompt migration.

A study of migrants in the Upper Senegal River Valley, where rain fed agriculture and livestock are major economic outputs, suggests that aggregate levels of migration remained the same during the 1983-1985 droughts, although the composition of the migrations changed. More costly moves (international destinations) declined from a pre-drought rate of 42% of migrants engaged in international moves to a drought-period rate of 27% of migrants taking part in international moves. At the same time, shorter distance and duration migrations saw a marked increase from 25% of respondents indicating a circular move pre-drought to 63% of respondents making a similar move during the drought period. These results suggest that strategic migration decision-making was taking place in response to climatic conditions, albeit on a local scale. The pattern of women and child migration also shifted during the drought. In the pre-drought period, 17% of children were migrating compared to 24% during the drought-period. Women were also migrating at an increased rate, 34% of women were migrating during the drought period compared to the 17% of women migrants during the pre-drought period. These increases in migration among women and children may have served as a means to reduce pressures on households during declining agricultural outputs (Davis 1963; Findley 1994).

Migration following climate change may also be a household strategy in Burkina Faso, in response to fluctuations in rainfall declines and harvest yields, but in this case significant results are only seen when destination of the move is considered. Otherwise, when all destination types are modeled together, individual characteristics such as education level, economic activity and ethnic group are significant determinants of out-migration; environmental factors such as rainfall have no significant effect on whether someone migrates. When the destination is specified and considered along with rainfall data, results indicate that men and women who live in drier regions are far more likely to make a temporary move, but generally only to a neighboring rural area. Longer distance moves are generally not considered by migrants from rain-scarce regions, instead these moves are more likely to come from people living in wetter regions where water limitations are less of an issue (Henry, Schoumaker, and Beauchemin 2004). These results suggest that in both Mali and Burkina Faso, declines in harvest production due to drought discourage longer distance, temporary migrations. Longer distance, permanent moves from Mali and Burkina Faso to urban areas occur, but are not influenced by changing environmental conditions (Findley 1994; Henry, Schoumaker, and Beauchemin 2004). In both of the preceding studies the assumption is that migration is influenced by climate change and the proxy measure is rainfall amounts and perceptions of drought and their impact on the decision to different destinations. The Burkina Faso study is also limited in that it only considers first migration moves, so little is known about circular migration in response to prolonged climatic stress. Furthermore, the underlying or pre-existing patterns of migration and the conditions or institutions that generate and fuel those patterns are not taken into account in these studies.

Gray (2009) argues that a dichotomous modeling approach may conceal more subtle heterogeneity in migration patterns. A study of migration, using a multinomial discrete-time event history model, examines the role of drought in the southern Andes region of Ecuador. This study contributes to the literature on environmentally-drive migration by examining the influence of both environmental factors and land ownership on three types of migration destinations (local, internal, and international). Previous studies examining drivers of migration behavior have focused on land ownership and others have looked at the role of the environment, Gray's work combines these two influences to gain additional insight into what motivates migration behavior when land is undergoing change. In his study, when an unusual harvest (defined by Gray as a harvest that is reported as unusually good or bad, since either type of harvest appeared to influence migration patterns) was indicated, the odds of migrating both locally and internally increased and are significant while the odds of migrating internationally in the face of harvest fluctuations is not significant. Internal migration is associated with low levels of land ownership and access to social networks, but it is not as sensitive to changes in environmental conditions (Gray 2009). The focus on destination type reveals differential drivers of migration and corroborates findings from Mali and Burkina Faso that show that environmentally-driven migrations are overwhelmingly local. Gray and Mueller (2011) extend this modeling strategy to study a similar migration phenomena in rural Ethiopia, this time adding motivation (labor, marriage, other) to examine how motivations change under drought conditions (Gray and Mueller 2011).

Finally, research on environmental change in Nepal by Massey, et al. (2007) also concludes that environmentally-induced migration is restricted to local moves (within versus outside of the Chitwan Valley) and that male and female migrants respond differently to environmental change. A perceived decline in agricultural productivity raises the odds of a local move by 30% and a smaller share of the respondent‘s neighborhood covered in green increases the odds of moving locally by 2%. Finally, for every hundred minutes of additional time to gather firewood, the odds of making a local move increases by 6%. All of these variables are used to capture environmental stress, and are significant factors that predict a local move. A gendered division of labor in the study area translates to a gendered risk of migrating, depending on which household task is impacted by environmental change. Men typically collect the firewood and women collect the fodder; both tasks can be impacted by environmental conditions and when additional time is needed to collect firewood, the odds of men migrating are 12%, while a woman‘s odds of migrating is not impacted; when time spent on collection of fodder increases, women‘s odds of migrating out of the valley increases by 14% while men‘s odds of migrating unaffected by this gain in time (Massey, Axinn, and Ghimire 2007). These results, in addition to the differential patterns of local versus longer-distance migrations, suggest migrant selectivity in the environmental change and migration literature, namely that of gendered divisions of labor and how these modes of labor might be differentially impacted by climate change The work reviewed highlights attempts made at capturing human response over a short time-scale; it also reveals that the relationship between slower-onset climate change and migration is complex.

Specifically, subsequent to initial empirical work and mixed results about the impact of climate change on migration, scholars in the field now call for measures of climate change that distinctively observe both slow-onset change and short-term extreme events (Pigeut 2010). Furthermore, as migration scholars have recognized for a decade or more, an array of migration outcomes need to be observed in order to evaluation climate change impacts, including the timing and duration of permanent, temporary, circular or seasonal, and return migration. However, few data are available to allow such observations and to model this complexity.

Many of the papers examining migration outcomes rely on rainfall data as a proxy for environmental change (Barrios, Bertinelli, and Strobl 2006; Gray 2009; Henry, Schoumaker, and Beauchemin 2004; Myron, Deane, Lauster, and Peri 2005), while some rely on self-reporting of drought by the survey respondents (Findley 1994; Gray and Mueller 2011), or disaster reports (Halliday 2006; Saldaña-Zorrilla and Sandberg 2009). Time use studies are employed in two studies of environmental change and migration in Nepal to provide proxy measures of environmental stress. Length of time (in minutes) to collect firewood and fodder are considered and compared to time to perform similar tasks in the years preceding the study (Massey, Axinn, and Ghimire 2007; Shrestha and Bhandari 2007). In other instances and where the data are available, spatial measures of rainfall have also been used. While deviations from normal rainfall are a good way to capture environmental perturbations, particularly in areas that rely on rainfall for irrigation, indicators of longer-term water stress on vegetation may provide a more nuanced picture of longer-term livelihood impacts due to water shortages. Furthermore, rainfall data are captured with weather stations that are frequently widely dispersed on the landscape, requiring significant assumptions in order to interpolate the impact of rainfall across the landscape and between points.

To our knowledge, only two papers use NDVI to proxy the natural resource base available to those who rely on the environment for their livelihoods in any given year. In their examination of the influence of typologies of environmental conditions on migration, Henry et al. (2004) combine rainfall data and NDVI to conduct survival analyses to investigate the influence of both drought and longer-term land degradation (captured via NDVI as a measure of NPP or net primary production) on migration behavior. They find that 82% of the population that migrated out of rural areas came from another rural area where longer-term land degradation is occurring, compared to 57% of migrants from rural areas where rainfall is below a normal level. Their results suggest that slower-onset land degradation may be a better predictor of migration response than relying on rainfall data alone (Henry, Piché, Ouédraogo, and Lambin 2004).

Van der Geest, et al. (2010), in their cross-sectional analysis of migration and environment in Ghana also employ NDVI and rainfall amounts to determine their association with migration from North to South Ghana. However, the paper does not go beyond describing associated trends in NDVI, rainfall, and migration patterns over the study. Further estimation models may indicate a causal relationship between the various data presented (Van der Geest, Vrieling, and Dietz 2010). We extend current knowledge by combining a longitudinal dataset with local (NDVI) and global (ENSO) environmental data to investigate the impacts of environmental change on migration patterns. In the future, we hope to include rainfall data to our analysis, landscape information, and land cover interpretations in order to better model more proximate stress (rainfall) with longer-term vegetative stress (NDVI).

We contribute to this small but growing literature with an analysis of longitudinal data covering over one hundred thousand person-year-moves, representing thousands of individuals from rural Nang Rong, in NE Thailand, over a 16-year period. Using geo-referenced residence information we match these demographic data to 26 years of environmental information about local vegetation health and episodic cycles of global climate – namely the El Niño-La Niña effects (a.k.a. ENSO or El-Niño Southern Oscillation).

Nang Rong, in the northeast region of Thailand, is a good choice for a study site because of the history of internal migration in the area, a former frontier region that has undergone considerable land use and population changes during the latter half of the twentieth century (Entwisle, Malanson, Rindfuss, and Walsh 2008). Nang Rong has also been the focus of extensive study and much is known about the motivations and consequences of circular labor migration from the area. Considerable quantitative and qualitative data have also been collected on the environment and migration in Nang Rong (Curran et al. 2005; Garip 2008; Van Wey 2003; Rindfuss et al. 2002). Seasonal migration is common in Nang Rong, where the rainy, monsoon season is often followed by drought-like conditions that require people to migrate in search of non-agricultural labor to supplement their incomes and family's livelihoods.

We use two environmental indicators to predict migratory behavior, at the global and local levels: El Nino Southern Oscillation (ENSO) events and Normalized Difference Vegetation Index (NDVI). NDVI allows us to examine long-term vegetation changes in the area and determine the role these changes play in migratory decisions. ENSO data allows us to examine to what extent global processes that yield extreme oscillations in climate outcomes then impact migration behavior in an area of the world that is particularly dependent on monsoonal rains for rice cultivation and therefore vulnerable to the drier impacts of an El Niño event. Both NDVI and ENSO events offer more robust measures of environmental stress than rainfall measures alone (more typically used in analyses of climate change, drought and migration, e.g. Findley 1994). While we are not measuring migration in any more complex ways than previous studies, our data are unlike those of previous work because they are prospective and observe climate variability and migration patterns over a 16-year period, rather than cross-sectional or over two time periods.

We expect that when summarized monthly variability in the typical global climate patterns fall outside the modal tendency that these are relevant and influence migration behavior. Specifically we expect that when a majority of months prior to the time in question and the timing of a potential move are predominantly under the influence of El Niño events then a person is at higher risk of migrating out of the region. On the other hand, we expect that when a majority of months prior to the time in question and the timing of a potential move are predominantly under the influence of La Niña events then the risk of migration will be lowered significantly. Similarly, when NDVI annual patterns indicate significant plant stress and drought then we expect higher out migration, whereas when NDVI patterns indicate significant rainfall and then dramatic green-up (e.g. high plant health) we expect to see much lower risks of migration.

DATA AND METHODS

Nang Rong Study Area (see Figure 1)

Nang Rong, Buriram is located in the southern portion of the northeastern region of Thailand. The district is transected through the middle by a national highway running west to east and connecting Bangkok to the Laotian border on the eastern side of the nation. The Nang Rong district is primarily agricultural relying on a variety of crops for subsistence consumption and market destinations both within the district and for export to the capital and beyond. It is located on the Korat Plateau which is characterized by relatively infertile soils, poor drainage and inconsistent precipitation (Walsh et al. 2001). Rainfed rice cultivation is typical in the lower elevations and corn, cassava, sugar cane, and forest products in the upper elevations (Curran and Cooke 2008; Walsh et al. 2001). In all cases, there is very limited irrigation, if any. Walsh et al. (2001) describe the landscape as follows:

Over time, the lowlands were transformed into a landscape matrix dominated by rice paddies, isolated trees in and around the paddies, riparian forests, and forests retained near village compounds. In the uplands, forests (dry deciduous dipterocarp forest) still are a really significant, but cash crops now comprise substantial areal proportions of the area. The juxtaposition of multiple households and clusters of villages create a landscape matrix in which individual rice paddies coalesce into extensive tracks throughout the lowlands. In the uplands, cash crops occur in either extensive and generally uninterrupted tracks, in small clusters of fields, or in singular plots associated with individual households or a small cluster of households distributed across the landscape. The middle and high terraces, positioned between the lowlands and uplands, may serve as the fulcrum between two differing habitats that inter- mix along this transitional gradient depending upon labor, capital, crop prices, and monsoonal efficacies. Reforestation is also occurring as a consequence of secondary plant succession, government reforestation programs in conservation forests, and the retainment of forests in and around villages and near rivers and streams. The landscape matrix and its temporal and spatial context is the product of a set of complex and interacting processes that extend across the social, biophysical, and geographical domains.

In general the land is highly vulnerable to drought and prone to unsustainable agro-ecological conditions (Welsh 2008). The predominance of environmental stress in the ecological system figures prominently in the narratives of villagers (Curran and Sawaengdee 1998; Curran et al. 2005). These narratives are also prominent throughout the northeast region of Thailand and explain much of both historic and contemporary migration flows out of the region and to metropolitan or ecologically richer regions of the country (Chamratrithirong et al. 1995). It is the preponderance of local explanations combined with the contemporary global discussions about climate variability and migration that motivates our inquiry.

Nang Rong Migration Data

Our migration data come from the Nang Rong Surveys, a longitudinal panel data collection effort conducted by the Carolina Population Center at the University of North Carolina and the Institute for Population and Social Research at Mahidol University in Thailand.[1] We employ the first three waves of data (collected in 1984, 1994, and 2000) for our analyses. The 1984 data collection was a census of all households and individuals residing in 51 villages within Nang Rong. It included information on individual demographic data, household assets and village institutions and agricultural, natural, economic, social, and health resources. Further, village-level data were collected from all of the villages in Nang Rong district. The 1994 survey followed all 1984 respondents still living in the original village, as well as respondents from 22 of the original 51 villages who had moved to one of the four primary destinations outside of the district, plus any new village residents. The 1994 surveys included all questions from the 1984 survey, as well as a 10-year retrospective life history about education, work, and migration, a

[1] The data and information about the surveys are available at http://www.cpc.unc.edu/projects/nangrong/

survey about the age and location of siblings, and a special survey of migrants' migration experiences and histories. The 2000 round of surveys built on the previous data collection efforts by following all of the 1994 respondents and adding to the database any new residents and households in the original villages.

The 1994 and 2000 surveys included a migrant follow-up component. This was conducted among persons who had resided in 22 of the original 1984 villages, and defined a migrant as someone who was a member of a 1984 household and had since left a village for more than two months to one of four destinations: the provincial capital, Buriram; the regional capital, Korat or Nakhon Ratchasima; Bangkok and the Bangkok Metropolitan Area; or Eastern Seaboard provinces. The migrant follow-up in 2000 included migrants identified and interviewed in 1994, and individuals who had lived in the village in either 1984 or 1994 but subsequently migrated to one of the four primary destinations. The retrospective recall items in the survey allow us to measure timing and sequencing of moves (outgoing and returning), migrant destination, occupation in destination, and duration of stay. The data for these analysis focus only upon villagers from the 22 villages where there was a migrant follow-up component. In these villages, the follow-up rate is fairly high (about 78%) because the survey team relied on a multiple search methods (see Rindfuss et al. 2002). This means that migrant selectivity bias is minimized among this group of villagers and villages.

Our analysis file relies primarily on the data found in the life history modules implemented in both 1994 and 2000. With these data we construct an analysis file that is comprised of person-year-move records. For each individual we have information about their sequence of residences and moves within a year for the preceding 10 years in the case of the 1994 survey and for the preceding six years for the 2000 survey. Retrospective life histories were collected for most individuals who had ever resided in Nang Rong in any 1984, 1994 or 2000 household and who were 13-44 years old at some point during this time period. Our analyses examine individual behavior prospectively from 1984 and 1994 to 2000 and do not include individuals who newly appear in households in 2000.

We measure migration as any move outside of the Nang Rong district for 2 months or more. Figure 2 displays the trends of migration among those at risk of migrating in any year for each village. What can be observed from Figure 2 is that there is a great deal of variation across the 22 villages there is a general trend of increasing migration between 1990 and 1998, with drop-off after 1998. However, villages located variously across the landscape appear to follow very different trends annually with some exhibiting relatively high levels of migration in a year and others lower levels. In other studies, it has been shown that the cumulative patterns of migration are quite different across villages, with some villages exhibiting quite steep trajectories of accumulated migration experience and others exhibiting much lower rates of increase (Curran et al. 2005; Garip and Curran 2009; Garip 2008). Figure 2 also shows that there is some fluctuation within villages across time.

In order to take into account and control for underlying currents of migration trends that might be explained by a host of other factors, besides environmental conditions, we also control for migration histories and migration experiences at the individual and village level. While not perfect proxies for alternative explanations for migration patterns, prior migration prevalence is a well-known measure of cumulative migration and the temporal ordering partially allays endogeneity concerns. Separately, we estimate the number of trips made by a person up through year t-1, the number of months experienced as a migrant by that person up through year t-l, the number of trips made by other community members up through year t-1, the months of experience accumulated by other community members through year t-1. The community migrant trips and months of migrant experience do not include the experience of the observed individual (for details please see Curran et al. 2005)

ENSO: A Global Environmental Measure

We employ El Nino Southern Oscillation (ENSO) data as our global environmental measure and to proxy year effects in our regression analysis. ENSO is a key source of interannual variation in weather and climate in the world, and the subject of much study (Trenbeth and Caron 2000; Wolter and Timlin 2011). ENSO occurs roughly every two to seven years and ENSO impacts differ depending on the region of the world. In Thailand, El Nino events result in warmer, drier conditions, while La Nina events lead to cooler, wetter conditions. Prior to 1980, there was little correlation between monsoonal rainfall totals in Thailand and ENSO events, Singhrattna ,et. al. (2005) found that post-1980, due to a shift in circulations patterns, there is now a strong link between rainfall variability during summer monsoons and ENSO in Thailand however (Singhrattna, Rajagopalan, Clark, and Krishna Kumar 2005). As a result, Thailand is now particularly susceptible to fluctuations in the sea surface temperate in the Pacific Ocean, resulting in a decline in summer monsoon rainfall. Farmers rely on the summer monsoons to irrigate their fields, so we anticipate that in years where the preceding summer monsoon rainfall totals were lower, we will see an increase in the odds of out migration. On the other hand, during La Nina periods when conditions are cooler and wetter than normal, we anticipate a decrease in the odds of out migration. To our knowledge, few studies have examined the impacts of ENSO events on migration patterns in agricultural areas that rely on reined agriculture. A case study of Ecuador that is part of a larger European Union study on Environmental Change and Forced Migration (EACH-For) includes results of qualitative fieldwork that suggests people may have migrated due to the 1997 El Nino event, but no quantitative study has been conducted to verify these claims (Gila, Dieguez, and Zaratiegui 2009).

We use the Oceanic Niño Index from the National Weather Service's Climate Prediction Center. The data is reported as 3-month running averages of sea surface temperatures in the Nino 3.4 region (5oN-5oS, 120o-170oW). Warm (El Niño) and cold (La Niña) episodes are noted when temperatures remain 0.5 degrees Celsius above or below normal temperatures for 5 overlapping 3-month periods. Figure 3 shows a sample of the data we use to create summary measures of the ENSO effects. Specifically, we derive a measure of accumulated El Niño or La Niña by counting the number of preceding months (counting back 12 months and 24 months) from the start of the typical land preparation and beginning of rice cultivation, usually in May for most farmers in the region. We then calculate the portion of the preceding 12 or 24 months that is characterized by one or the other event or the absence of either event (which we categorize as a neutral event month). In Figure 3 these month-events are coded red for El Niño and blue for La Niña. We chose a threshold of 50% of the months, to capture the predominant modal ENSO event, and coded for each of these preceding time periods for each type of event. For example, if in the preceding 12 months, six months or more were El Niño events then we coded those pixel-year observations as El Niño. We coded all pixel-years either as predominantly El Niño, La Niña, or neutral (neither event). We followed the same procedure for the preceding 24 months. Distinguishing between the preceding 12 months and 24 months of accumulated events provides an opportunity to evaluate how more information and more intense experiences of events may differently influence behavior. We suspect that farmers and farm families might be particularly influenced to make a migratory move if there are two years of predominantly droughty climate experiences, as opposed to only one.

<u>NDVI Local Environmental Measure</u>

We used the Normalized Difference Vegetation Index (NDVI) to examine how the localized changing conditions of vegetation health across Nang Rong may play a role in migratory decisions. NDVI has been used for many years to monitor the photosynthetically active biomass and growth (vigor) of plant canopies from satellite remote sensing imagery (Tucker et al. 1985), and is becoming increasingly popular as a tool to assess vegetation's response to environmental change (Pettorelli et al. 2005). This vegetation index compares the intensity of light reflected in two regions or "bands" of the electromagnetic spectrum: 1) Red, where chlorophyll causes considerable absorption, and 2) Near-infrared, where spongy mesophyll leaf structure creates considerable reflectance (Tucker 1979). NDVI is calculated as the difference between the values of the near-infrared and red bands divided by the sum of the values of these same bands. Vigorously growing healthy vegetation has low red-light reflectance and high near-infrared reflectance, and hence, high NDVI values.

The long-term Global Inventory Modeling and Mapping Studies (GIMMS) NDVI dataset was chosen for this study because its historical vegetation health record completely overlaps the time span of the Nang Rong migration data. GIMMS provides 24 full years (1982 – 2006) of global bimonthly NDVI data (24 measures per year) compiled from a series of National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) satellites and instruments.[2] This dataset has been corrected for calibration, view geometry, volcanic aerosols, and other effects not related to vegetation change (Tucker et al. 2005). The primary drawback of the GIMMS data is its coarse scale (low spatial resolution), with unique values reported for every 8km x 8km area (pixel). While this offers a limited number of observation regions (7x7 or 49 pixels) for the Nang Rong study area (Fig. 1), the spatial variability in vegetation health provided by GIMMS still provides a far more detailed look at the environment than

[2] GIMMS data and documentation available at http://www.landcover.org

the single global measure provided by ENSO. What GIMMS NDVI dataset lacks in spatial resolution it makes up for in temporal resolution, or measurement frequency. Most remote-sensing-based studies of landscape change employ imagery data resources as longitudinal or panel analysis data. For several dates throughout the study period satellite imagery is used to derive NDVI for each pixel or to classify each pixel into one of many land-use or land-cover (LULC) categories. These NDVI or LULC classification data are then used as indicators of the landscape state at specific moments in time, or compared to one another to derive change trajectories. In contrast, the GIMMS data provides enough samples of NDVI to permit a more complete look at the yearly vegetation health cycle as demonstrated by plots showing the NDVI curve shape for several pixels in Nang Rong (Fig. 4). In Figure 4, we show the pixel coverage for NDVI for the Nang Rong district. We also show the villages captured in each pixel with the red circles. And, following a transect from the southwest corner to the northeast corner of the district, a line that starts in the uplands and moves towards the lowlands we show the annual monthly trends of NDVI signals for 1994, 1995 and 1996 for each pixel.

Taken together, each yearly set of NDVI values from a pixel (visualized by the shape of a plot) show a unique signature of vigor (stressed, normal, or highly productive) of the land cover type(s) at that location (rice paddy, upland crop, forest, etc.). Because there are so many points of data across time, we have 49 pixels and 26 years of data, in our study we used a simple unsupervised (i.e. fully automated) clustering approach to group similar “pixel-years” of NDVI data for the entire Nang Rong District for comparison to yearly migration rates of individuals within villages. For the clustering algorithm we chose model-based clustering, specifically the finite Gaussian mixture models estimated by the MCLUST package in R (Fraley and Raftery 1999). This package uses Bayes factors to optimize the finite mixture model over the number of mixtures considered and the covariance matrix of the variables included in the model.

For each of the 49 pixels in the study area, our clustering approach used the twelve monthly averages of NDVI values for an entire Thai “Water Year” (May – April of the following year) to correspond with monsoon-based seasons and crops (Crews-Meyer, 2004). We allowed a maximum of 20 clusters with BIC scores determining the optimal number of clusters. Given their location, each village could be associated with a pixel and its corresponding cluster for each year of the study. Figure 5 displays the full range of clusters that are derived from the data and unsupervised modeling approach. There are nine statistically different clusters of NDVI annual patterns that appear to show quite different signals of wetness, green-up, and drought. Cluster 1 is the modal cluster for most pixel-years. It shows a bump up or green up during months Aug-October, an expected increase that is expected given the end of the monsoonal season and the resulting vegetation growth, particularly in rice paddies. Other clusters show steeper inclines in green-up indicating possibly strong and health vegetative growth, particularly clusters 3, 6 & 9. Clusters 2 & 4 show two periods of green-up, also indicating possibly relatively robust vegetative growth. Our interpretations of these clusters are necessarily speculative as we do not yet have land cover information to calibrate our understanding of these signals.

The development of this measure is significantly different both substantively and methodologically from previous uses of NDVI in predicting migration outcomes. Rather than using a single signal and interpreting plant stress, we consider the collective pattern of signals reflecting vegetation health over the entire agricultural year from land preparation to planting, harvesting and fallow. With this measure we also are attempting to capture the retrospective viewpoint of farmers assessing the livelihood risks of agricultural decisions over the past year as they might influence their subsequent decisions for the next year. Similar to our ENSO models, we expect that these year long retrospections are better estimates of what influences a farmers' intuition-driven assessment which then influences an individual's and members of a household's behavior.

<u>Explaining Migration Using Event History Models</u>

The empirical papers to date, modeling migration and environment dynamics, have employed various statistical methods to model the impact of drought or environmental change on migration behavior. Findley's study of the impact of drought on migration in Rural Mali uses bivariate regression analysis to compare migration types, migrant destinations, and the age-sex composition of migrants (Findley 1994). Others rely on post-event case studies to ask how people responded to drought (Gilbert and McLeman 2010; Van der Geest, Vrieling, and Dietz 2010). A number of papers use event history analysis models to measure the odds of a migration event (Gray 2009; Gray and Mueller 2011; Henry, Schoumaker, and Beauchemin 2004; Massey, Axinn, and Ghimire 2007). We build on these latter approaches to prospectively estimate migration, using a frailty model, which is a special case of an event history model to model circular migration in our study area. Event history or survival analysis is a special type of analysis for longitudinal data that is concerned with the duration of time that a person, institution, or group remains in one state (survives) or transitions to another state (failure), while under exposure to a set of covariates of interest (risk). Put another way, the dependent variable is the conditional probability that an event will occur at time t. Event history models are the appropriate models to use in cases where the data is incomplete, meaning that the process of interest hasn't occurred for all individuals under observation before the period of observation has ended. These right-censored observations are incorporated into the calculation of the conditional probability in a way that would not be possible if we were to rely on OLS linear regression methods. Event history models allow us to estimate parameters for a model without having to exclude right censored observations; removing the right censored observations would seriously bias the estimate of the hazard probability that we are interested in. (Box-Steffensmeier & Jones 2004; Mills 2011)

Frailty models can be considered random effects models for survival analysis. Frailty terms are specified in the model to explicitly account for extra variance in the data that is associated with unmeasured risk factors (Box-Steffensmeier and Jones 2004). Frailty models are models where the underlying hazard function is modified to include random effects and unobserved heterogeneity, as well as potential cluster effects that result when a portion of the dataset is more likely to be at risk of failure. They are a special case of the Cox proportional hazard, a semi-parametric model commonly used in EHA.

Shared frailty models consider clusters of individuals that share some frailty that makes them more susceptible to the influence of covariates in the model. The underlying hazard rate of one cluster looks different than the hazard rate of another set of clusters, and the model used needs to take these divergent hazard structures into account when parameter estimates are calculated. Shared frailty models are also used when there is some correlation among individuals in a cluster. (Box-Steffensmeier and De Boef 2006) argue that for repeated events in survival analysis, a conditional (shared) frailty model should be included, to account for three things common to repeated events: individual-level heterogeneity, event dependence, and both individual-level heterogeneity and event dependence together. According to the authors, “The conditional frailty model allows for the possibility that both heterogeneity and event dependence make important contributions to the hazard rate or an individual’s risk for a particular event (re)occurrence” (Box-Steffensmeier & De Boef, 2006: p 3523).

The specification of our models follows:

$$\boxed{h(t \mid x_{ij}, v_j) = h_0(t) v_j \exp(x'_{ij} b)}$$

We estimate four models, including a base model explaining out migration. For the base model of controls we include measures of age (measured with two terms – age and age-squared), sex, educational attainment, marital status, migration experience (including measures of accumulated migration experience among the individuals themselves and other community members), household land ownership, and village remoteness from main towns and roads. We then test three models to test the impact of climate variability. The first estimates the impact of accumulated impact of months of ENSO events for the preceding 12 months. The second estimates the impact of accumulated impact of months of ENSO events over the preceding 24 months to capture longer and more stressful or healthier climatic events. The third model estimates the influence of the cluster-based models of NDVI on migration impact.

RESULTS (VERY PRELIMINARY)

Table 1 provides descriptive statistics for the base model variables and the migration outcome measure. These results mirror those in previous studies using the Nang Rong Survey life history models. We provide descriptive statistic from several viewpoints, one for the beginning of the survey period, one for the end of the survey period and one for the total pooled sample of observations. It should be noted that 13 year olds age into the sample for each year and that is why the sample grows over time.

Figure 6 provides a simple bivariate description of the patterning of ENSO events and annual migration rates. What we find is that migration rates appear to be highly associated with higher numbers of El Niño month-events.

Table 2 presents the results of all four models. Our base model corresponds with previous results found in earlier studies (Curran et al. 2005; Garip and Curran 2009). In our model of the ENSO results, net of other factors, we find that over the preceding 12 months La Niña predominant years, i.e. cooler wetter years, reduce the odds of migration by more than 30%. The other types of years have little effect on the odds of migration. On the other hand, when estimating the impact of ENSO events over the last 24 months, net of other factors, that El Niño predominant years raise the odds of out migration by almost 1.4 times. Finally, the estimation of the pixel-year cluster coding indicates that clusters 2, 6, and 9 those that indicate wet signals (a drop in NDVI signal) and then a steep green-up lower the odds of out migration significantly, net of other factors.

DISCUSSION & CONCLUSION

For both the ENSO and NDVI datasets we are really only beginning to understand the nature and distributions of the data, allowing us to generate appropriate measures and methods to work with these data that are most appropriate for migration studies.

The ENSO variability and exposure are a possible measure that might be employed in other studies in the ENSO region. However, it is at such a large scale it only captures variability years. NDVI data are more promising option for a more refined examination of climate variability and local environmental conditions, because it affords more variation across pixels and years. With methodological validation it could be a resource for other sites with rich social data, but limited environmental data close to the same scale.

In our next steps, we plan to elaborate a more complex estimate of migration patterns, including taking into account destinations and circularity. We will also include controls for other contextual effects that influence pushes and pulls. And, we plan to draw upon our longitudinal qualitative data that represents villagers' perceptions from across the landscape about the environment and the reasons for migration. Finally, we also plan to explore alternative methods of sub-setting full NDVI pixel-years for clustering. While we used entire window of pixels encompassing Nang Rong for all dates present in GIMMS dataset, the coded pixel-years are limited to just those pixels that contain villages or those years relevant to migration study. We plan to explore how village location within particular pixels and near-ness to neighboring pixels might be used to better calibrate the influence of NDVI summary signals. We also plan to pursue a data-driven (supervised) clustering approach that incorporates land cover information and rainfall to provide clustering algorithm with "priors" of pixel-years of known landcover type.

FIGURES & TABLES

Figure 1: Study Site Map

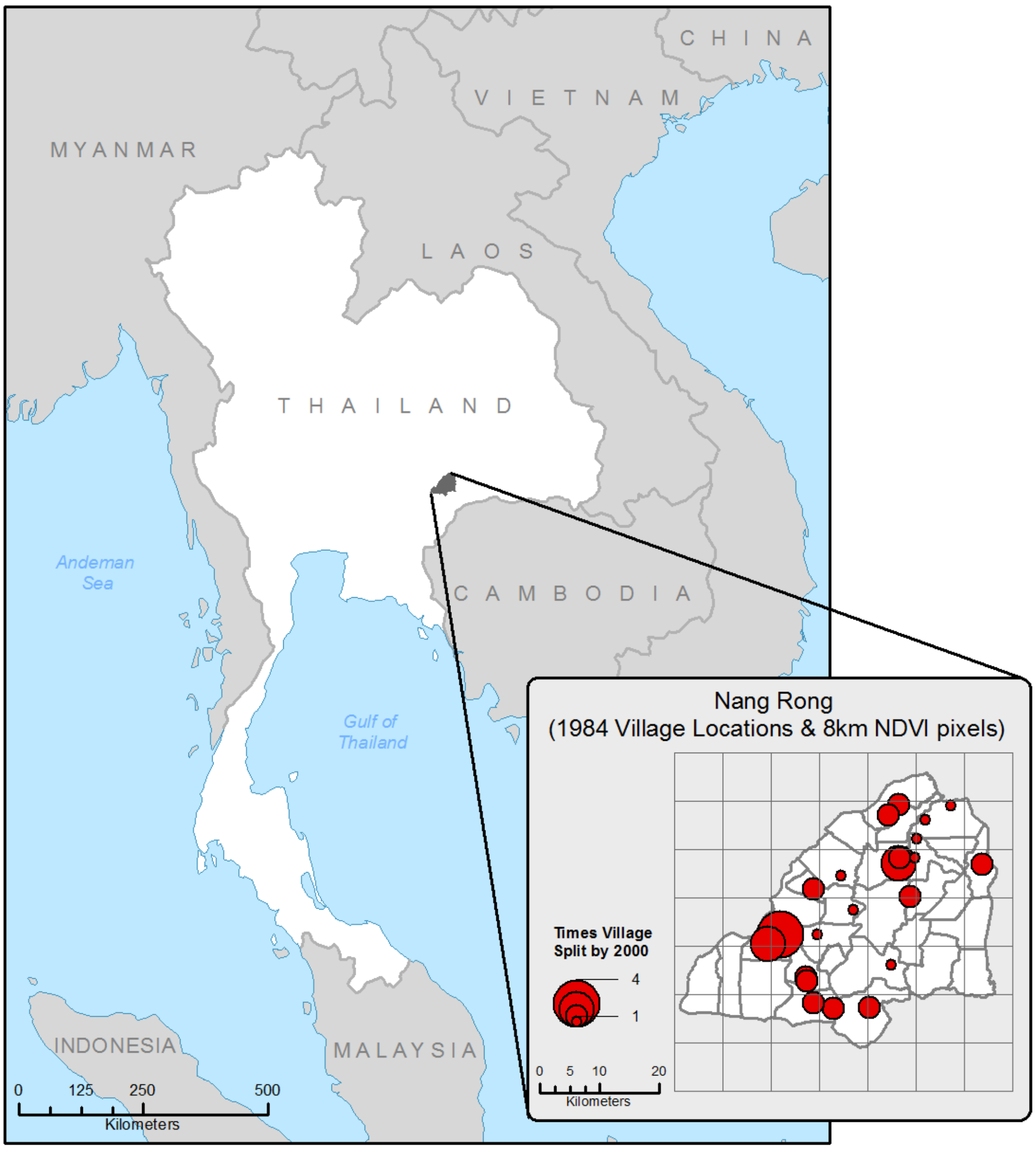

Figure 2: Annual trends in migration across the 22 study villages (% migrants among 13-45 year olds in each year, lines represent villages)

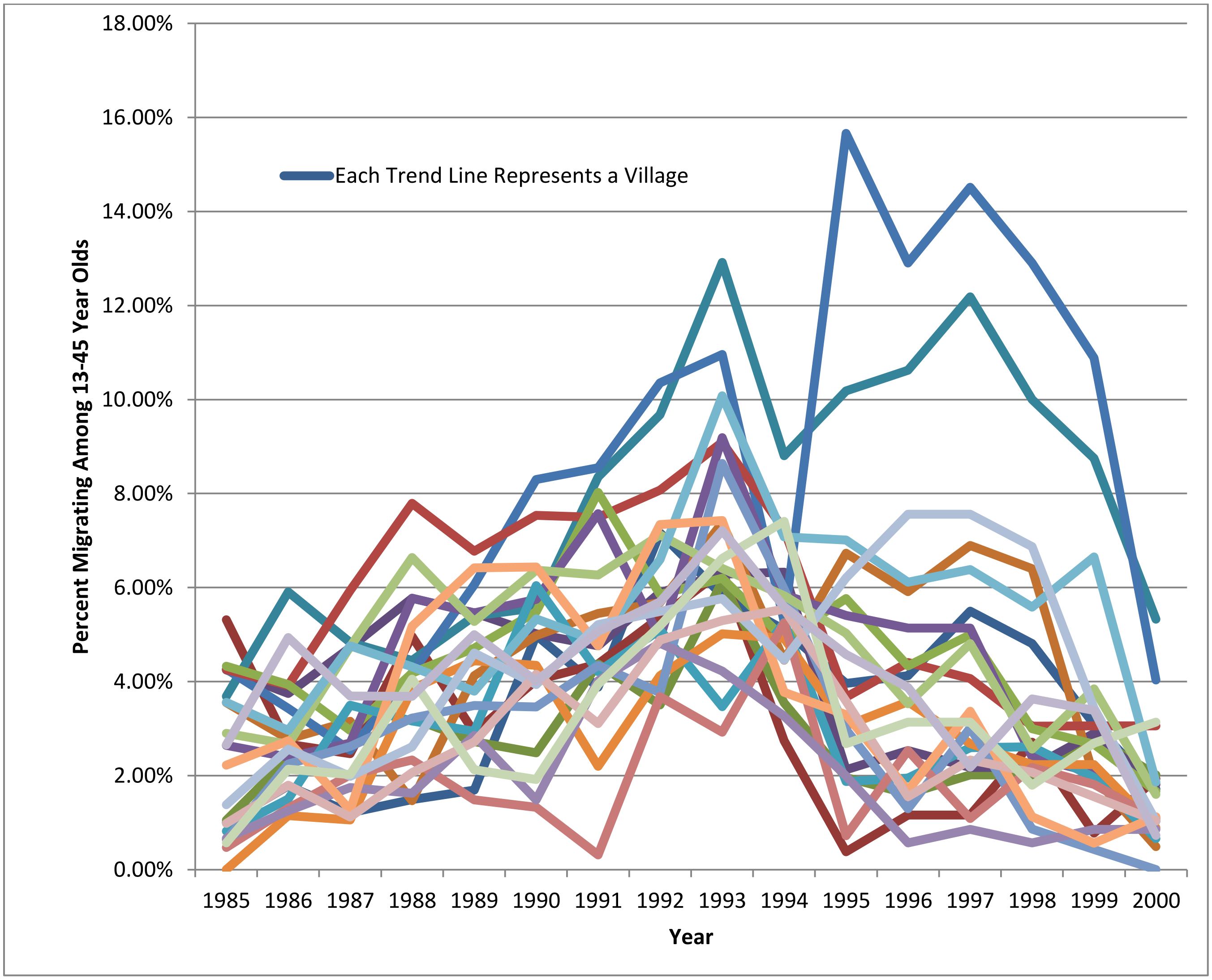

Figure 3: Sample of Yearly, 3-month averages of ENSO Index (blue indicates El Niño events, red indicates La Niña events)

(http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml)

3-Month Avg/Year	DJF	JFM	FMA	MAM	AMJ	MJJ	JJA	JAS	ASO	SON	OND	NDJ
1996	**-0.7**	**-0.7**	**-0.5**	-0.3	-0.1	-0.1	0	-0.1	-0.1	-0.2	-0.3	-0.4
1997	-0.4	-0.3	0	0.4	**0.8**	**1.3**	**1.7**	**2**	**2.2**	**2.4**	**2.5**	**2.5**
1998	**2.3**	**1.9**	**1.5**	**1**	**0.5**	0	**-0.5**	**-0.8**	**-1**	**-1.1**	**-1.3**	**-1.4**
1999	**-1.4**	**-1.2**	**-0.9**	**-0.8**	**-0.8**	**-0.8**	**-0.9**	**-0.9**	**-1**	**-1.1**	**-1.3**	**-1.6**
2000	**-1.6**	**-1.4**	**-1**	**-0.8**	**-0.6**	**-0.5**	-0.4	-0.4	-0.4	**-0.5**	**-0.6**	**-0.7**

Figure 4: Pixel Maps of NDVI Coverage and Sample Profiles for 1994, 1995, 1996

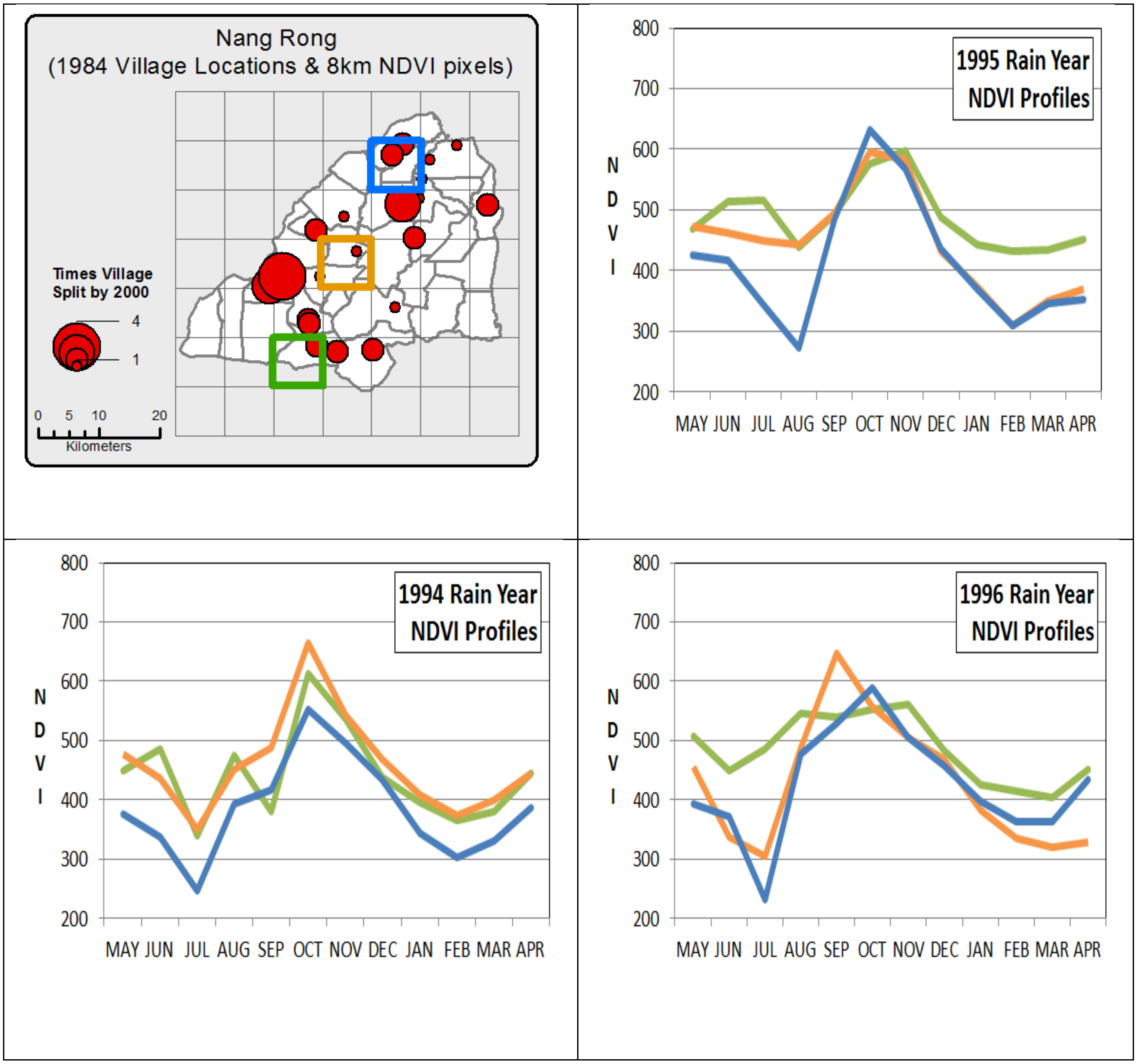

Figure 5:

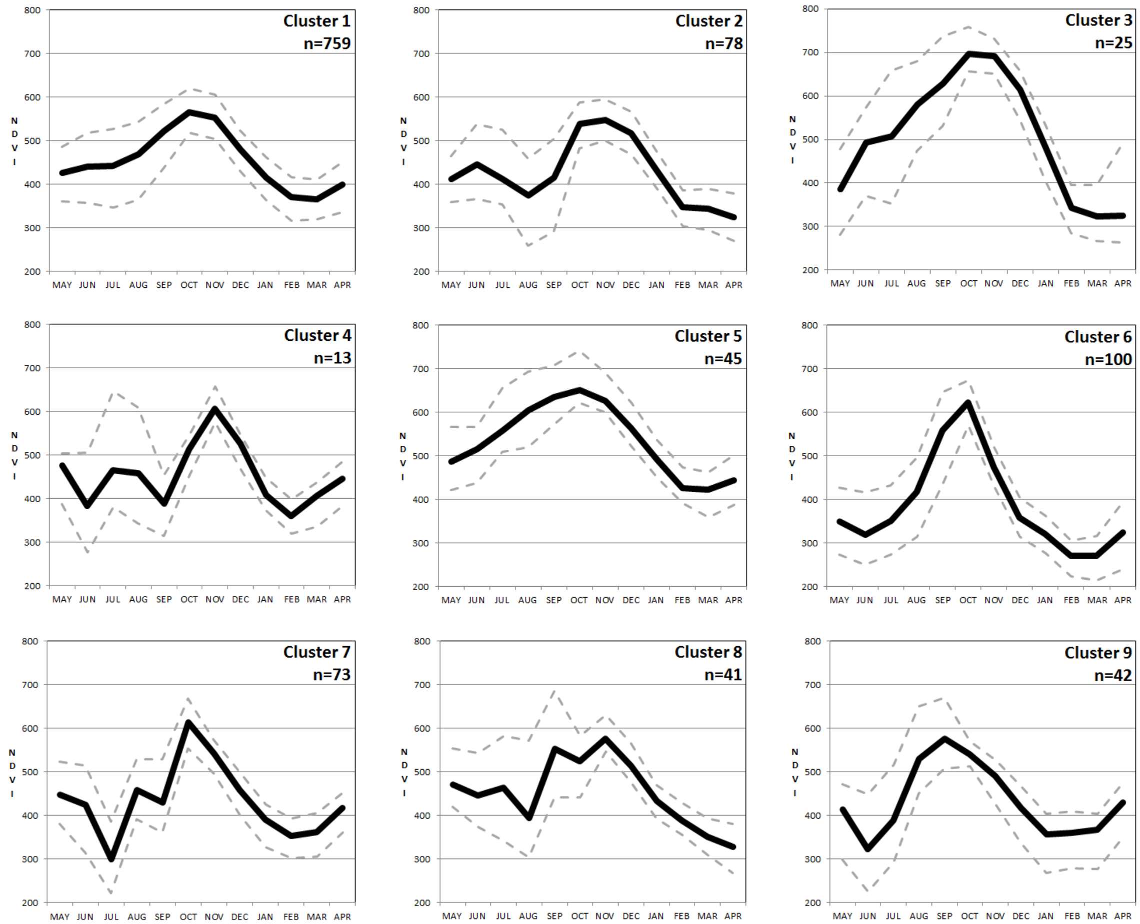
Cluster 1
n=759
Cluster 2
n=78
Cluster 3
n=25
Cluster 4
n=13
Cluster 5
n=45
Cluster 6
n=100
Cluster 7
n=73
Cluster 8
n=41
Cluster 9
n=42
NDVI
800
700
600
500
400
300
200
MAY JUN JUL AUG SEP OCT NOV DEC JAN FEB MAR APR

Figure 6: Number of Months of ENSO in Prior 24 Months and Percent Migrants Moving out of Nang Rong District (13-45 Year Olds)

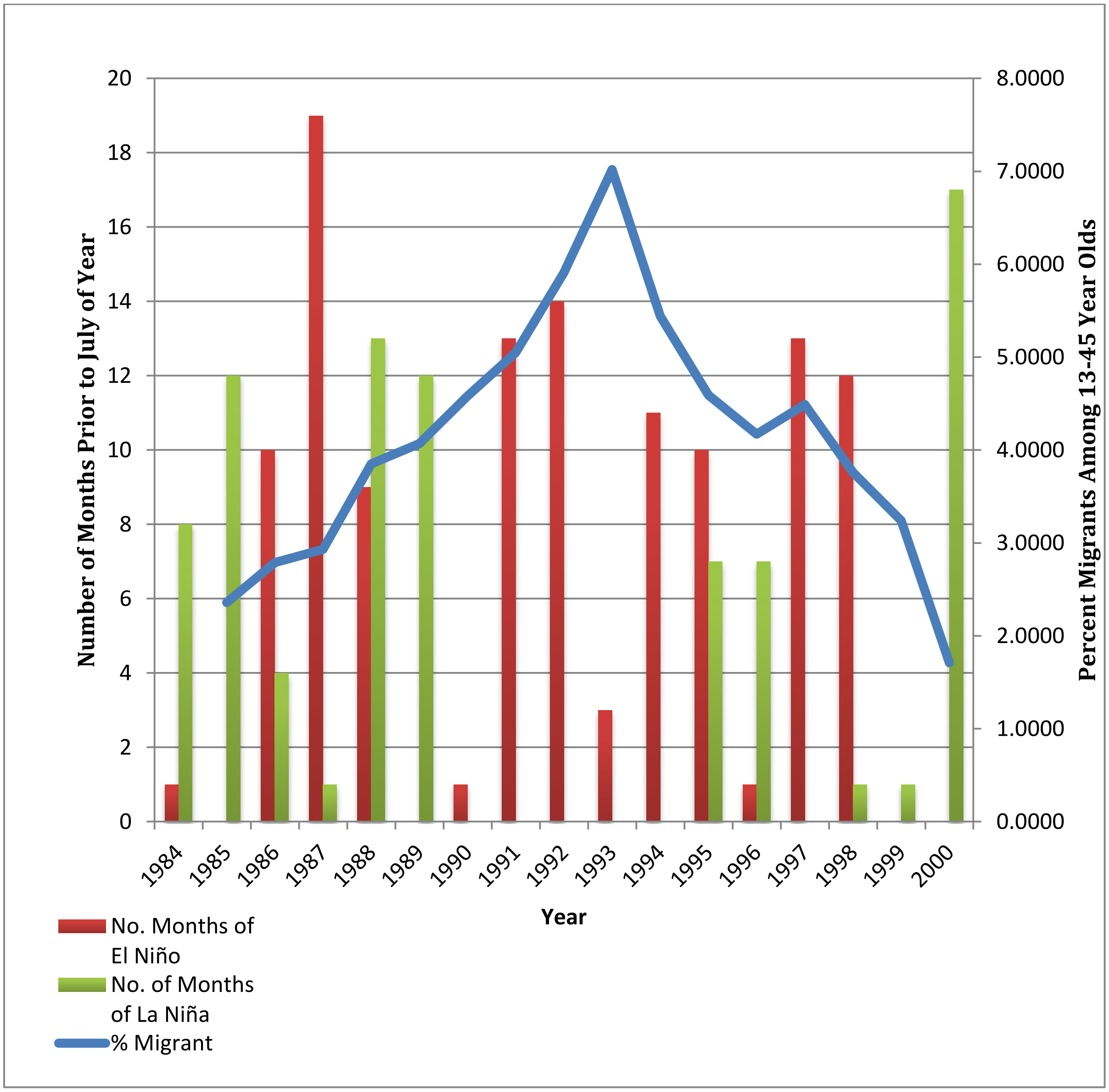

Table 1: Descriptive Statistics for Nang Rong Life History (1984, 2000)

	1985 N= 4572		2000 N=6141		All Years N=100408	
	mean	s.d.	mean	s.d.	mean	s.d.
Dependent Variable						
Migrate out of Nang Rong in Time t	0.024	0.152	0.017	0.130	0.043	0.202
INDIVIDUAL time-invariant						
Male (0/1)	0.511	0.500	0.461	0.498	0.488	0.500
Indiv was temp migrant in 1984	0.072	0.258	0.044	0.205	0.050	0.218
HOUSEHOLD time-invariant						
HH had any temp migrant 1984	0.163	0.370	0.137	0.344	0.141	0.348
HH owned no land in 1984	0.009	0.093	0.074	0.261	0.038	0.192
HH owned 10-25 rai in 1984	0.191	0.393	0.282	0.450	0.241	0.428
HH owned 25+ rai in 1984	0.341	0.474	0.331	0.471	0.326	0.469
VILLAGE time-invariant						
Village very remote	0.663	0.473	0.647	0.478	0.653	0.476
INDIVIDUAL time-variant						
Age	18.837	3.963	28.99	6.745	23.269	6.578
Age Squared	370.51	152.9	885.9	396.68	584.73	327.17
Married	0.458	0.498	0.690	0.463	0.596	0.491
Some secondary education	0.213	0.409	0.207	0.406	0.206	0.404
Finished secondary education	0.048	0.214	0.095	0.293	0.062	0.241

Indiv cum # mig trips, t-1	0.025	0.165	1.953	2.883	0.941	1.949
Indiv cum mig months, t-1	2.874	5.038	48.26	54.131	24.065	36.627
VILLAGE time-variant						
Village cum mig trips per person, t-1	0.025	0.016	1.893	0.460	0.909	0.609
Village cum mig months/person, t-1	2.86	0.74	51.47	9.33	25.54	15.30

Table 2: Event History, Frailty Model of Out Migration and Climate Variability

	Base		ENSO 12 mo.		ENSO 24 mo.		NDVI	
INDIVIDUAL time-invariant								
Male (0/1)	1.270	***	1.262	***	1.267	***	1.258	***
Indiv was temp migrant in 1984	0.831		0.830		0.830		0.821	
HOUSEHOLD time-invariant								
HH had any temp migrant 1984	1.038		1.044		1.041		1.053	
HH owned no land in 1984	0.865		0.859		0.891		0.855	
HH owned 10-25 rai in 1984	1.060		1.063		1.069		1.057	
HH owned 25+ rai in 1984	0.915	*	0.925	*	0.922	*	0.920	*
(HH owned 1-9 rai in 1984)								
VILLAGE time-invariant								
Village very remote	0.00001	***	0.00001	***	0.00001	***	0.000	***
INDIVIDUAL time-variant								
Age	1.139	***	1.128	***	1.136	***	1.131	***
Age Squared	0.997	***	0.997	***	0.997	***	0.997	***
Married	0.698	***	0.693	***	0.700	***	0.685	***
Some secondary education	0.708	***	0.706	***	0.711	***	0.700	***
Finished secondary education	0.745	***	0.746	***	0.744	***	0.762	***
Indiv cum # mig trips, t-1	1.195	***	1.196	***	1.195	***	1.196	***
Indiv cum mig months, t-1	1.005	***	1.005	***	1.005	***	1.005	***
VILLAGE time-variant								
Village cum mig trips per person, t-1	1.054		1.129		1.043		1.210	*

Village cum mig months/person, t-1	0.989 ***	0.989 ***	0.986 ***	0.989 ***
CLIMATE VARIABILITY				
GE 50% of last 12 months exp ENSO				
El Nino		0.957		
La Nina		0.669 ***		
Neutral		1.126		
GE 50% of last 24 months exp ENSO				
El Nino			1.349 ***	
La Nina			0.917	
Neutral			1.083	
NDVI Clusters				
Number 2				0.615 ***
Number 6				0.615 ***
Number 7				0.969
Number 8				0.904
Number 9				0.354 ***
(Number 1, omitted)				

* p<=.05; **p<=.01; ***p<=.005

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