PAA 2014 Paper Submission

Title: Who Perceives What? A Demographic Analysis of Subjective Perception in Rural Thailand

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Abstract

Rural households that rely on natural resources for livelihoods are expected to face increased vulnerability due to more frequent climate variability. A number of empirical papers assess the impact of environmental shocks on these households, including demographic research that investigates the impact of shocks of mobility. To date, few studies explicitly model how individual and household characteristics influence a household's subjective perception of environmental shocks. My paper uses a unique cross-sectional panel dataset from Rural Thailand to explore household composition and income, as well as community-level effects to predict a household's probability of reporting insufficient rainfall as a source of livelihood reduction. Preliminary results suggest that the composition of the household influences household response. Social learning may also play a role in household perceptual measures.

Introduction

The incidence of drought and floods, already a fact of life for residents in rural developing communities, is predicted to become more frequent and severe in the future, according to current climate models (IPCC 2007; Coe and Stern 2011). A substantial literature has emerged that theorizes, conceptualizes, and empirically identifies the most vulnerable of these populations, often relying on notions of vulnerability that are often assigned by outside researchers and development agencies, rather than assessing perceptions of vulnerability amongst target populations (Heijmans 2001). Vulnerability and adaptation to climate change research has made considerable advances towards understanding the complex relationship between human and environmental systems in an evolving climate (Cutter et al. 2009; Oliver-Smith 2009). Early research focuses on the severity of potential impacts to natural systems under proposed climate scenarios and tends to move in a linear fashion, examining the potential vulnerability as a relationship that moves in a direction from stressor to impacts, without considering more complex feedback loops that might better encapsulate conditions on the ground (Blaikie et al.1994; Turner et al. 2003; Eakin & Luers 2006). However, this singular focus gave way to more complex modelling of the linkages between humans and environmental systems (Fussel & Klein 2006; Turner et al. 2003). These more nuanced studies consider not only where potential impacts will occur, but also ask context-specific questions that consider how these shocks might be dampened or exacerbated by underlying societal conditions that leave an unequal portion of the population vulnerable to exogenous shocks, like adverse climatic events (Adger, 2006; Acosta-Michlik and Espaldon. 2008).

Today, social vulnerability research examines how differential socio-demographic characteristics can amplify or dampen the effects of environmental shocks on a given population (Cutter et al. 2009). Given two households situated in an area with similar environmental conditions, how do these two household experience and respond to environmental stress? One way to capture these differences is by asking households to reflect on causes of threats to household well-being. However, a tension remains in the vulnerability literature, between objective and perceptional characteristics of vulnerability, largely centered on conceptual debates that highlight difficulty in assessing household attributions (Adger 2006). As a result of this tension, questions that measure individual or household assessment of the role that the environment plays in a reduction in livelihoods are largely absent, despite calls for longitudinal studies that include questions about household experience with climactic shocks (Billsborrow 2009; Sanchez-Pena & Fuchs 2012).

To date, only a few studies model household risk assessments among rural households in the developing world, (Barett et al. 2001; Bunting et al. 2013; Doss et al. 2008; Hunter et al. 2010) or incorporate household reports of environmental exposure alongside objective measures of environmental stress to model adaptive measures undertaken by vulnerable households (Findley 1994; Gray and Mueller 2012; Massey et al. 2010). My paper addresses this gap in the vulnerability literature by explicitly exploring household casual attributions of a bad income year and the associated demographic characteristics across households that report the environment as a risk factor. In particular, how do rural located households across four provinces in NE and Central Thailand differ in their attribution of a bad income year to environmental causes? A household's assessment of the environment as a source of stress can reveal a lot about the level of exposure to environmental perturbations, as well as a household's resilience and ability to cope in the face of an environmental risk (Barrett at al. 2001). Addressing issues that are most salient to residents living in areas that are vulnerable to increases in exogenous shocks, such as drought or flooding, is key for policymakers interested in crafting sound policies to address the social impacts of climate change.

Background

A small literature explores subjective risk assessments in rural agricultural areas in the developing world, and these studies mainly focus on East and Southern Africa. Despite their different contextual settings, all four studies reviewed here make a strong case for the inclusion of local assessments of environmental conditions, as they uncover notable heterogeneity in perceptions of livelihood threats across relatively small geographic areas. Barrett et al. (2001) adds considerably to our understanding of subpopulations within a seemingly homogenous landscape, and how these subpopulations differentially experience risk. Their study, largely focuses on the construction of a risk assessment index following the administration of an open-ended survey that asks respondents to list and rank a variety of hazards that they perceive.

Several important contributions emerge from their study. First, from basic descriptive analysis, they identify cross-sectional heterogeneity in risk assessments across the individuals surveyed. In order to make sense of these differences, they argue that reports of risk assessments are composites of four key components: degree of objective exposure to a risk (place-specific, such as rainfall), individual perception (which can be conditioned by previous experience), and whether a respondent can apply *ex ante* mitigation or *ex post* coping strategies. The authors argue that these four components shape individual risk assessments, and can help explain differences among households living under the same level of environment exposure. Regressing risk assessments against various household characteristics, including location and gender, also adds complexity to the vulnerability literature. Comparing assessment of drought risk with rainfall, they find that drought is typically considered a significant risk by residents who live in areas where on average there is greater rainfall. This suggests that people who live in areas with more variable rainfall might engage in coping or mitigation strategies that are not present in areas with more reliable rainfall. This study suggests that risk assessment, in addition to objective data, provides a more complete picture about how the environment is experienced (Barrett et al. 2001). The limitation of Barrett et al.'s study is that it relies on cross-sectional data, which doesn't allow for observations of temporal variation and past experience and how these combine to update or extend risk assessments. Also, while they do test the effects of select household characteristics on risk assessments, they don't include many demographic characteristics of the households.

Doss et al. (2008) extend Barrett's work by analyzing household risk assessment in East Africa. In particular, they ask how these assessments differ among individuals and across time and space. Like Barrett et al., they assume respondent risk assessments can differ depending not only on exposure, but also depending on perception, and coping and mitigation strategies. Unlike Barrett et al. they include monthly observations measured over a period of 2.5 years, to investigate the role of partial updating and past experience in shaping risk assessments. They also include individual demographic controls such as age, gender, and headship, as well as household and community level controls. Regressions are run for only the top five risks identified, and food insecurity and loss of pasture, two conditions that co-vary with differential rainfall scenarios. The results of this study find that community-level variables have a significant effect on risk rankings, when controlling for household and individual-level characteristics, a factor that the authors attribute to information sharing and social learning. Similarly, community-level risks related to variable rainfall had a stronger impact on risk assessment than household-level risks did. Concerns also vary more across rather than within communities, and rankings changed across the 27 months of the study period, meaning that no one risk dominated the rankings (Doss et al 2008). These results add additional complexity to the vulnerability literature by highlighting that risks perceived by individuals can vary depending on a number of factors, including proximity of an event to when the survey is taken, as well as the influence of partial updating through social capital.

Hunter et al. (2010) find similar community-level impacts in their work that examines environmental concern among rural South African residents, arguing that despite the importance of the environment for the well-being of many rural residents, few studies exist that consider the influence of scale on attributions of environmental concern in the study site. The authors also consider heterogeneity across villages in the study setting, finding, like Doss et al. (2008) that factors that influence environmental concern operate at the micro-level. Village location is a significant factor in environmental concern in the study, as is gender, with female-headed households expressing environmental concerns closely related to tasks that they typically engage in within the household. Similar to the earlier work in East Africa, one limitation of this paper is that the analysis is limited to a single survey, so while it captures spatial heterogeneity, it doesn't allow analysis of how risk assessments might change over time, depending on time.

Bunting et al. (2013) expands on previous work reviewed above, in their study that analyzes perceptions of villagers in Botswana and Namibia using a risk hazards framework, organizing responses along the five asset categories defined by the Sustainable Livelihoods Framework (Carney 1998; Scoones 1998). They find that despite efforts to mitigate risk in the social, physical, and financial arena within the study area, factors related to climate variability, including droughts remain a significant threat to well-being, particularly among households identified as subsistence-based households. The authors add to the literature on risk assessments by including measures of the incidence of a given risk (measured as the proportion of respondents who identify a given risk as a concern) as well as severity index, to capture the degree to which the risk is considered a concern. Similar to other studies that explicitly model risk assessments, the main drawback of Bunting et al.'s study is the lack of temporal depth. The authors acknowledge the need for time series data to capture a more complete understanding of how self-reported threats and risk evolve over time (Bunting et al. 2013).

Barrett et al., Doss et al., Hunter et al. and Bunting et al. add considerably to our understanding of how community and household-level characteristics shape how residents assess risks to their livelihoods, including environmental factors. Collectively, these findings hint towards community-level environmental and social factors that result in heterogeneous environmental concern in a seemingly homogenous landscapes. Despite a relative deprivation or state of poverty among respondents in all three papers, there still operates distinct and significant localized notions of risk that suggest that future studies of risk assessment will benefit from a careful consideration of scale.

My paper contributes to the literature on vulnerability by analyzing data from an ongoing cross-sectional panel study of rural households in four provinces located in NE and Central Thailand. The unique nature of these data allows analysis of retrospective self-reports of vulnerability over time and across 14 districts, to identify which households consider the environment as a major impact to their livelihoods, and the effect that various household characteristics and location have on their stated risk assessment. Drawing on the Sustainable Rural Livelihoods Framework (Carney 1998; Scoones 1998), my paper draws on concepts presented in Bunting et al. (2013) to explore the influence of differential access to natural, social, financial, and human capital assets within a household to explore the question: does the probability of a household reporting the environment as a cause of a bad income year differ depending on location, and the suite of assets and demographic characteristics present in the household?

Data and Measures

Townsend Thai Data

The Townsend Thai Data is an ongoing cross-sectional stratified, clustered random sample panel data set that was designed to investigate the impact of informal institutions such as family and social networks on livelihood outcomes in households located in two provinces in Northeast and Central Thailand. (Townsend et al. 1997). The survey grew from an initial cross-sectional survey in 1997 to an annual survey, with a small subset of households surveyed monthly. Four provinces were selected for the survey to acknowledge regional differences in the various measurements of interest, two in the Northeast and two in Central Thailand. 64 villages are surveyed in total, with 15 households surveyed in each of the villages, totaling 960 households a year.[1] The main unit of analysis of the survey is at the household level, but household rosters are collected that ask a number of demographic questions, including sex, age, education and occupation of household members that allow me to generate household composition variables to analyze the impact of household structure on my variable of interest. My paper draws on a number of modules from the annual survey to generate the variables analyzed here, in particular questions from the Risk Response survey module are used to generate my dependent variable. The question asked of all households is: Comparing this past year (e.g. June 2002 – May 2003) to the year before that (June 2001 – May 2002), which was the worst year for household income? Households that indicate the past year to be the worst for income are prompted to supply the first and second most important reasons that they believe explains why their income was lower in the past year.

For my paper, I only analyze the various household and community characteristics that might influence a household indicating insufficient rainfall as a cause of a bad income year. My justification for restricting the analysis to this response is two-part. First, out of the 4,768 (N=9576) household-year observations in my dataset that responded that the year that had just past was the worst income year, 1,551 households (32.5%) reported "not enough rainfall" to be the main reason. Second, I am particularly interested in understanding the relationship between household characteristics and subjective perceptions of household vulnerability to environmental stress. A more detailed vulnerability assessment that includes additional causal attributions is beyond the scope of this present study. Table 1 lists the frequency of attributions given to explain a bad income year.

Important to note is that the survey questionnaire only asks the respondent to indicate the most important reason for a decline in income. There are additional pieces of

[1] For more detailed information about the design of the dataset, please see: http://cier.uchicago.edu/data/data-overview.shtml

information that had it been collected would have lent itself to a more nuanced study. For example, from the questions there is no way to model magnitude of the shock, or if the response to “not enough rainfall” represents not enough in absolute quantity, or not enough in terms of timing. This is an important distinction that I am not able to control for, without qualitative interviews to clarify how the respondent interprets the question. The timing of the survey may also influence the responses given, as annual resurveys are conducted in May, which comes at the end of the dry season in the NE and Central Thailand.

NDVI

Incorporating earlier environmental data into a study of human response to the environment allows researchers to generate baseline trend variables, an important component in a study that considers subjective perceptual measures in a given year, relative to environmental trends in the immediate and more distant past. The Global Inventory Modelling and Mapping Studies (GIMMS) normalized difference vegetation (NDVI) dataset provides 24-years (1982 to 2006) of global bi-monthly (24 measures each year) vegetation changes, obtained via images produced by National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) satellites and instruments, measured in 8km x 8km pixels. While the spatial resolution is coarser than the resolution of more recent NDVI products, the strength of these data lies in the rich temporal resolution, which combines well with longitudinal social data. NDVI is a measure of plant biomass and general health, obtained from satellite remote sensing imagery (Tucker et al. 1985), and is being used more frequently as a way to assess the impact of climate environmental change on plant health (Pettorelli et al. 2005). NDVI is a ratio of light reflectivity in the red and near-infrared bands of the electromagnetic spectrum, and give an indication of how much of the photosynthetically active bands of light are being absorbed by vegetation on the ground:

$$NDVI = (NIR - RED) / (NIR + RED)$$

Red, where chlorophyll causes considerable absorption, and 2) Near-infrared, where spongy mesophyll leaf structure creates considerable reflectance (Tucker 1979). Actively growing healthy vegetation tends to reflect less red light, and more near-infrared light, so that a higher NDVI value can be interpreted to mean healthier plan. NDVI can be used to assess drought by examining the NDVI anomaly, defined as the difference in a monthly or annual measure as compared to a longer-term average for the same time period (Anyamba et al. 2005). An annual NDVI measure for each amphoe (district) where the households are located is generated. I calculate a period (1997 to 2006) average and then create standardized z-scores to indicate yearly anomalies from the period average NDVI. Table 2 shows how each district's NDVI differs from the period average, by year.

Measures

Sustainable Rural Livelihoods Framework and Independent Variable Selection

The Sustainable Rural Livelihoods Framework, though initially conceptualized to study the differential determinants of chronic poverty, as a means to devise policy prescriptions to reduce it, is a suitable framework to investigate elements of households within a population that may also be vulnerable to the impacts of environmental shocks. The strength of this framework is the exploration of differential access to a series of assets (human, natural, social, physical, and financial) and entitlements that can highlight both vulnerability to environmental risk, but also the available assets within a household to help adapt to risk (Bunting et al. 2013; Carney 1998; Eakin and Luers 2006; Scoones 1998). I draw on this framework to inform variable selection for my model, and argue that access to these various forms of capital may protect a household from the negative impacts of an environmental stress, or conversely, may help to explain which household characteristics make households more likely to report an environmental stress as a dominant threat to household livelihoods.

Human capital represents the various skill sets and available labor within a household, and depends on the mix of age, education, and labor force participation. To model these factors, I include controls for the age, sex, and education level of the head, as well as a variable that measures the percent of household members engaged in agriculture as their primary occupation. In order to capture the influence of the age and gender effects on household composition, I include a number of variables that measure the influence of younger and older working-age males and females present in the household, as well as the number of children and elders present. While the dependency ratio is a well-established measure of the ratio of dependents in the household relative to working age members, I am interested in understanding how a more refined measure of age structure might inform how a household considers the environment as a threat to their livelihoods. Previous work on household composition and family life course transitions in rural China finds that younger households, and younger males in particular, are more likely to engage in more innovative labor reallocation strategies during a period of reform (Chen and Korinek 2010). I adapt Chen and Korinek's modelling of household composition to empirically test whether households with younger members might influence how a household experiences and reports environmental stress. Men and women in Thailand have different roles and expectations within a rural household, although there is evidence that these strict gender roles that had previously tied women to rice growing and other agricultural duties within the household is waning as non-farm economic opportunities expand. (Curran and Saguy 2001; Curran et al. 2005; Garip and Curran 2010). Despite these changing gender notions, it is still possible that the relative presence of men and women of early and later working age may influence the probability of a household reporting a lack of rainfall as a primary concern.

I use an indicator variable to control for annual changes in natural capital in the district where the household is located. Using a period-average NDVI value for each district, I indicate whether the household located in that district experienced a normal year, or had a drier or wetter year relative to the period-average. This physical measure allows me to analyze how household-level assessments of risk respond to shocks in the district. Both Doss and et al. (2008) and Hunter et al. (2010) find that social learning, or "learning from others" may influence how individuals and households assess risk, so I include a variable that asks households to assess whether the preceding year was a bad year for others in the village.

Households that respond that they share resources, such as rice, money, equipment or labor with non-relatives might be less likely to reply that they had experienced a bad year and to attribute this cause to the environment. A rich literature exists that analyzes the role of informal sharing on consumption patterns and income shocks (Fafchamps & Lund 2003; Townsend 1994), pointing to the reliance on these informal institutions as a coping mechanism. I test whether a household that shares resources, net of other household controls, has an effect on the probability of a household reporting a bad year due to the environment.

Finally, in addition to annual income measures, I include a control for whether a household is a member of an agricultural cooperative or the Bank for Agriculture and Agricultural Cooperatives (BAAC). Households with access to borrowing instruments may have different assessments of a risky year than households that lack such credit. There is some evidence that membership in a cooperative may add to the resilience of a community. Townsend, in an evaluation of various village institutions finds evidence that membership in BAAC and agricultural cooperatives do show positive benefits in terms of consumption smoothing during idiosyncratic shocks, which include rainfall deficits (Townsend 2013).

Model and Results

I use a random-effects logit model to assess the effect of household characteristics on the probability that a household's bad income year in the previous 12 months was due to "not enough rainfall". Households that indicated another reason for a bad income year, and households that either replied their income was the same, or that the past year was a better income year relative to two years ago, are assigned a 0 value for this variable. I include village-level fixed effects in my model to account for potential similarities of households in the same villages. Table 3 shows the mean of all households in each district, by year that attribute their bad income year to "not enough rainfall."

I estimate three models: a base model with only household characteristics, a second model that includes the district-level measure of NDVI anomaly and the variable that asks households to assess whether others in the village also had a bad year. Finally, in the third model, I add the social sharing (I limit this to sharing rice for this initial analysis) and financial institution membership variables. Results of these three models are provided in Table 6. In each of the models, the significant household characteristics that predict an increase in the odds of a household declaring "not enough rainfall" as the primary reason for a bad income year are: the age of the head of the household, the percentage of household engaged in agriculture as a primary occupation (with no members of a household engaged in agriculture as the referent), the total number of females aged 25 to 59, and the number of elders present in the household. The perception that other households in the village suffered a bad income year, and the district-level NDVI deviation from a normal year were also significant predictors of a household attributing insufficient rainfall as the cause of a poor income year. My measures of social sharing and financial institution membership do not significantly predict a household attributing a bad rainfall year. Finally, relative to the referent category of the lowest income quintile, the odds of reporting the environment as the cause of a bad income year decreases as a household's income quintile increases.

Discussion and Future Research

This preliminary analysis of the effect of household characteristics on the odds of a household attributing a bad income year to not enough rainfall is similar to previous research on environmental risk assessments. Doss et al. (2008) find little significance at the individual or household-level, aside from income, and that variable is not significant across all risk classes. However, in both Hunter et al. (2010) and Doss et al. (2008), community and village-level effects did lead to a reporting of an environmental shock. In my models, including the respondent's perception of how others in the village fared significantly increased the odds that the household attributed a bad year to not enough rainfall. This suggests that social learning might be a factor in how people form their perceptions about what causes a bad year, holding the district-level NDVI values constant. On the other hand, this might point to micro-level differences in rainfall that might not be captured in a district-level measure of environmental conditions.

While the sex of the household head was not significant, the presence of females between the ages of 25 and 59 and elders within the household increase the odds that a household reported “not enough rainfall” as a cause of a bad income year. The presence of males in the household was not significant, regardless of whether they are part of the younger or older age group. The presence of children in the household is also not significant. This suggests that older female household members might be tied to the household via childrearing or agricultural duties, and are therefore more sensitive to perceived changes in environmental conditions. Further investigation into occupation by gender and age might give additional insight into these issues.

In my models, households with higher levels of income had lower odds of reporting lack of rainfall as the primary threat to livelihoods (income). While this makes intuitive sense, it also suggests that another measure, such as a wealth index, might better capture longer-term status of the household. Tesliuc and Lindert (2004) in a report on vulnerability to a variety of shocks in Guatemala construct a wealth index using PCA to overcome the potential spurious relationship between poverty and shocks. My next iteration of this analysis will include such a wealth index. Similarly, the higher the percentage of household members engaged in agriculture as a primary occupation (relative to household with no one engaged in agriculture) significantly increases the odds of a household reporting lack of rainfall as a threat to their livelihoods. It is interesting to note that the middle category, 30 to 59% has the higher odds relative to the referent category. This variable is currently an aggregation of all types of agricultural workers. Future versions of this model that disaggregates the type of agriculture might tease out a more nuanced story of how agricultural participation influences

The lack of significance of the financial cooperative variable also warrants further investigation of the role that membership in this type of institution plays in a household’s on risk assessments. Kinnan and Townsend (2012), analyzing data collected monthly from a subset of villages surveyed in the annual Townsend Thai Data, find that access to financial capital is important, but this access might come through informal social channels, rather than through a household's direct membership.

Despite some of the limitations and need for further research, I argue that the preliminary results add to our understanding of which households are likely to report an environmental shock, such as insufficient rainfall, which is common in the study area. Next steps include refining some of the measures used in this model, as well as a separate study that incorporates subjective measures of rainfall to model household-level migration.

Works Cited

Adger, W. N. (2006). Vulnerability. *Global Environmental Change, 16*(3), 268-281.

Acosta-Michlik, L., & Espaldon, V. (2008). Assessing vulnerability of selected farming communities in the Philippines based on a behavioural model of agent's adaptation to global environmental change. *Global Environmental Change, 18*(4), 554-563.

Anyamba, A., & Tucker, C. (2005). Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981–2003. *Journal of Arid Environments, 63*(3), 596-614.

Barrett, C., Smith, K., & Box, P. (2001). Not necessarily in the same boat: Heterogeneous risk assessment among East African pastoralists. *Journal of Development Studies*, *37*(5), 1-30.

Bilsborrow, R. E. (2009). *Collecting Data on the Migration-Environment Nexus.* In Laczko, Frank & Aghazarm, Christine (Eds.), *Migration, Environment and Climate Change: Assessing the Evidence* (pp. 115-96). Geneva: International Organization for Migration

Blaikie, P., Cannon, T., Davis, I. and Wisner, B.: 1994, At Risk: Natural Hazards, *People's Vulnerability and Disasters*, Routledge, London.

Bunting, E., Steele, J., Keys, E., Muyengwa, S., Child, B., & Southworth, J. (2013). Local Perception of Risk to Livelihoods in the Semi-Arid Landscape of Southern Africa. *Land, 2*(2), 225-251.

Carney, D. (1998). *Sustainable rural livelihoods: what contribution can we make? Papers presented at the Department for International Development's Natural Resources Advisers' Conference, July 1998.* Paper presented at the Sustainable rural livelihoods: what contribution can we make? Papers presented at the Department for International Development's Natural Resources Advisers' Conference, July 1998.

Chen, F., & Korinek, K. (2010). Family life course transitions and rural household economy during China’s market reform. *Demography*, *47*(4), 963-987.

Coe, R. and R. D. Stern. 2011. "Assessing and Addressing Climate-Induced Risk in Sub-Saharan Rainfed Agriculture: Lessons Learned." *Experimental Agriculture* 47(Special Issue 02):395-410

Curran, S. R., and A. C. Saguy. (2001) "Migration and cultural change: a role for gender AND social networks?." *Journal of International Womens Studies* 2(3): 54-77.

Curran, S. R., Garip, F., Chung, C. Y., & Tangchonlatip, K. (2005). “Gendered migrant social capital: Evidence from Thailand”. *Social Forces*, *84*(1), 225-255.

Cutter, S. L., Emrich, C. T., Webb, J. J., & Morath, D. (2009). Social vulnerability to climate variability hazards: A review of the literature. *Final Report to Oxfam America*, 1-44.

Doss, C., McPeak, J., & Barrett, C. B. (2008). Interpersonal, intertemporal and spatial variation in risk perceptions: Evidence from East Africa. *World Development*, *36*(8), 1453-1468.

Eakin, H., & Luers, A. L. (2006). Assessing the vulnerability of social-environmental systems. *Annual Review of Environment and Resources, 31*(1), 365.

Fafchamps, M., and S. Lund (2003). "Risk-sharing networks in rural Philippines." *Journal of development Economics* 71(2): 261-287.

Findley, S. E. (1994). Does Drought Increase Migration? A Study of Migration from Rural Mali during the 1983-1985 Drought. *International Migration Review, 28*(3), 539-553.

Füssel, H.-M., & Klein, R. J. (2006). Climate change vulnerability assessments: an evolution of conceptual thinking. *Climatic Change, 75*(3), 301-329.

Garip, F., & Curran, S. (2010). "Increasing migration, diverging communities: changing character of migrant streams in rural Thailand". *Population research and policy review*, *29*(5), 659-685.

Gray, C. L., & Mueller, V. (2012). Natural disasters and population mobility in Bangladesh. *Proceedings of the National Academy of Sciences, 109*(16), 6000-6005.

Heijmans, A. (2001). *Vulnerability: a matter of perception*. London: Benfield Greig Hazard Research Centre.

Hunter, L. M., Strife, S., & Twine, W. (2010). Environmental perceptions of rural South African residents: The complex nature of environmental concern. *Society and Natural Resources, 23*(6), 525-54

IPCC. 2007. "Climate Change 2007: Synthesis Report." Vol.: World Meteorological Organization.

Kinnan, C., and R.M. Townsend (2012). "Kinship and Financial Networks, Formal Financial Access and Risk Reduction". *American Economic Review*, 102(3): 289-93

Massey, D. S., Axinn, W. G., & Ghimire, D. J. (2010). Environmental change and out-migration: Evidence from Nepal. *Population and Environment*, *32*(2-3), 109-136.

Oliver-Smith, A. (2009). "Nature, Society, and Population Displacement: Toward an Understanding of Environmental Migration and Social Vulnerability. UNU-EHS InterSections

Pettorelli, N., Vik J.O., Mysterud, A., Gaillard, J.M., Tucker, C.J., Stenseth, N.C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change Trends in Ecology and Evolution, 20 (9) , pp. 503-510.

Sancez Pena, L ., & R, Fuchs. (2013). "Using household surveys in climate change vulnerability and adaptation analysis" In M. G & S. D (Eds.), *In The Demography of Adaptation to Climate Change,* (pp. 96-14). UNFPA

Scoones, I. (1998). Sustainable Rural Livelihoods: A Framework for Analysis. Brighton: Institute of Development Studies at the University of Sussex.

Tesliuc, E. D., & Lindert, K. (2004). *Risk and vulnerability in Guatemala: A quantitative and qualitative assessment*. Social Protection, Labor Markets, Pensions, Social Assistance, World Bank.

Townsend, R., principal investigator with Paulson, A., Sakuntasathien, S., Lee, T. J., and Binford, M., (1997) Questionnaire Design and Data Collection for NICHD Grant Risk, Insurance and the Family and NSF grants, The University of Chicago http://hdl.handle.net/1902.1/21635

Townsend, R. M., (1994) ''Risk and Insurance in Village India,'' Econometrica, 62(3): 539-591.

Townsend, R. M. (2011). *Financial Systems in Developing Economies: Growth, Inequality and Policy Evaluation in Thailand*. Oxford University Press

Tucker, C. J., Vanpraet, C. L., Sharman, M.J., and Van Ittersum. G. (1985). Satellite remote sensing of total herbaceous biomass production in the Senegalese Sahel: 1980–1984. Remote Sensing of Environment, 17, 233–249.

Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences, 100*(14), 8074-8079

Table 1 Frequency of Stated Reasons for Bad Income Year

	Frequency	Percent	Cumulative
Flood	287	6.02	6.02
not enough rainfall	1,551	32.53	38.55
pests destroy crop	102	2.14	40.69
crop yield low for some other reason	618	12.96	53.65
fire destroys house and/or equipment	3	0.06	53.71
low price for output	566	11.87	65.58
high input prices	263	5.52	71.1
education expenses are higher	99	2.08	73.18
need extra money for ceremony	27	0.57	73.74
income lower because of retirement	16	0.34	74.08
high investment costs	146	3.06	77.14
high expenses because of illness	136	2.85	79.99
building expenses are higher	44	0.92	80.91
death in family	36	0.76	81.67
worked fewer days in current occupation	493	10.34	92.01
bad year for household business	136	2.85	94.86
lost money gambling	2	0.04	94.9
unable to repay debt	12	0.25	95.16
grow a new crop	1	0.02	95.18
good weather for farming	2	0.04	95.22
worked more days in current occupation	1	0.02	95.24
Other	227	4.76	100
Total HH-years Bad Income Year	4,768	100	
Total HH- years in Sample	9,576		

Table 2 Standardize NDVI Anomaly by District and Year

Province	District	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Buri Ram	Prakhon Chai	2	-1	0	1	0	0	-1	0	-1	0
Buri Ram	Satuk	1	0	0	1	0	1	1	0	-2	-1
Chachoengsao	Bang Nam Prieo	2	1	1	0	-2	-1	1	0	-1	0
Chachoengsao	Phanom Sarakham	0	0	1	1	0	0	1	1	-2	-1
Chachoengsao	Pleng Yao	-1	-1	1	1	0	-1	1	1	-2	0
Chachoengsao	Tha Ta Kieb	1	-1	2	1	-1	-1	0	1	-1	0
Lop Buri	Chai Badan	1	-2	1	1	0	0	1	0	-2	0
Lop Buri	Khok Samrong	1	-2	1	1	1	0	0	0	-2	0
Lop Buri	Muang Lop Buri	1	0	1	1	-1	-1	1	-1	-2	0
Lop Buri	Tha Luang	0	-1	1	1	0	0	1	0	-2	0
Sisaket	Khantharalak	1	1	1	1	0	0	-1	0	-2	0
Sisaket	Kharnthararom	1	-1	2	-1	0	-1	0	1	-1	0
Sisaket	Khun Han	0	2	1	0	0	0	-1	0	-2	0
Sisaket	Prang Ku	1	0	0	1	0	1	0	0	-2	-1

Table 3 Mean # of HH by Year and District Responding "Not Enough Water"

		1997		1998		1999		2000		2001	
Province	**District**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
Buri Ram	Prakhon Chai	0.052	0.222	0.492	0.502	0.126	0.333	0.108	0.312	0.033	0.180
Buri Ram	Satuk	0.470	0.501	0.336	0.474	0.475	0.501	0.600	0.492	0.067	0.250
Chachoengsao	Bang Nam Prieo	0.017	0.129	0.117	0.324	0.000	0.000	0.017	0.129	0.017	0.130
Chachoengsao	Phanom Sarakham	0.050	0.220	0.233	0.427	0.119	0.326	0.033	0.181	0.050	0.220
Chachoengsao	Pleng Yao	0.085	0.281	0.283	0.454	0.117	0.324	0.033	0.181	0.000	0.000
Chachoengsao	Tha Ta Kieb	0.083	0.279	0.333	0.475	0.117	0.324	0.050	0.220	0.033	0.181
Lop Buri	Chai Badan	0.050	0.220	0.283	0.454	0.133	0.343	0.017	0.129	0.167	0.376
Lop Buri	Khok Samrong	0.083	0.279	0.200	0.403	0.183	0.390	0.067	0.252	0.183	0.390
Lop Buri	Muang Lop Buri	0.052	0.223	0.067	0.252	0.068	0.254	0.017	0.129	0.050	0.220
Lop Buri	Tha Luang	0.053	0.225	0.633	0.486	0.333	0.475	0.067	0.252	0.183	0.390
Sisaket	Khantharalak	0.033	0.181	0.067	0.252	0.300	0.462	0.250	0.437	0.033	0.181
Sisaket	Khanthararom	0.283	0.454	0.033	0.181	0.200	0.403	0.350	0.481	0.000	0.000
Sisaket	Khun Han	0.000	0.000	0.117	0.324	0.322	0.471	0.233	0.427	0.017	0.129
Sisaket	Prang Ku	0.167	0.376	0.150	0.360	0.850	0.360	0.667	0.475	0.033	0.181

		2002		2003		2004		2005		2006	
		mean	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
Buri Ram	Prakhon Chai	0.100	0.301	0.008	0.091	0.067	0.250	0.050	0.219	0.042	0.201
Buri Ram	Satuk	0.067	0.250	0.017	0.129	0.442	0.499	0.142	0.350	0.300	0.460
Chachoengsao	Bang Nam Prieo	0.050	0.220	0.000	0.000	0.050	0.220	0.200	0.403	0.033	0.181
Chachoengsao	Phanom Sarakham	0.050	0.220	0.100	0.303	0.033	0.181	0.250	0.437	0.083	0.279
Chachoengsao	Pleng Yao	0.133	0.343	0.050	0.220	0.033	0.181	0.267	0.446	0.033	0.181
Chachoengsao	Tha Ta Kieb	0.117	0.324	0.050	0.220	0.000	0.000	0.250	0.437	0.017	0.129
Lop Buri	Chai Badan	0.033	0.181	0.133	0.343	0.083	0.279	0.400	0.494	0.283	0.454

Lop Buri	Khok Samrong	0.367	0.486	0.050	0.220	0.133	0.343	0.400	0.494	0.217	0.415
Lop Buri	Muang Lop Buri	0.200	0.403	0.067	0.252	0.017	0.129	0.117	0.324	0.133	0.343
Lop Buri	Tha Luang	0.100	0.303	0.183	0.390	0.150	0.360	0.317	0.469	0.233	0.427
Sisaket	Khantharalak	0.250	0.437	0.150	0.360	0.217	0.415	0.583	0.497	0.433	0.500
Sisaket	Khanthararom	0.000	0.000	0.000	0.000	0.017	0.129	0.150	0.360	0.517	0.504
Sisaket	Khun Han	0.100	0.303	0.017	0.129	0.200	0.403	0.433	0.500	0.183	0.390
Sisaket	Prang Ku	0.017	0.129	0.000	0.000	0.233	0.427	0.183	0.390	0.050	0.220

Table 4 Agricultural Labor and Income Quintiles (Percentages)

	1997	*1998*	*1999*	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*
No Agriculture Labor	40.62	35.97	40.17	38.54	32.57	37.6	38.85	34.58	35.52	36.04
1 to 29 %	9.76	13.76	12.66	12.71	12.73	10	8.75	10	12.92	13.85
30 to 59%	26.83	28.05	27.09	27.92	28.6	27.81	24.27	28.96	28.23	28.23
60% +	22.8	22.21	20.08	20.83	26.1	24.58	28.13	26.46	23.33	21.88
Income Quintile	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1	32.34	29.44	30.86	29.69	26.2	26.88	17.92	17.29	18.85	19.79
2	21.42	24.53	23.54	23.54	24.74	21.98	23.75	20.52	20.83	16.46
3	20.78	18.48	18.31	17.81	18.06	20.21	21.15	19.48	18.54	20.63
4	13.15	14.09	14.12	16.04	16.28	14.79	19.38	23.54	22.5	22.81
5	12.3	13.47	13.18	12.92	14.72	16.15	17.81	19.17	19.27	20.31

Table 5 Household Composition (Percentages)

VARIABLE	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
NUMBER OF CHILDREN (0-14)										
0	29.06	27.74	26.26	29.9	30.48	32.19	34.79	35.31	35.63	37.6
1	30.01	31.7	33.47	32.19	33.82	31.46	31.77	31.46	32.81	31.77
>=2	40.93	40.56	40.27	37.92	35.7	36.35	33.44	33.23	31.56	30.63
NUMBER OF MALES AGED 15-24										
0	66.17	67.88	66.32	66.15	66.28	66.88	69.06	70.94	73.33	73.75
1	25.03	23.15	25.31	25	25.16	25.83	25.73	24.38	22.5	21.98
>=2	8.8	8.97	8.37	8.85	8.56	7.29	5.21	4.69	4.17	4.27
NUMBER OF FEMALES AGED 15-24										
0	69.03	68.51	68.62	68.85	69.42	69.69	71.67	70.73	72.71	74.69
1	24.39	25.13	23.43	23.96	23.28	24.38	23.75	25.21	23.13	22.29
>=2	6.57	6.36	7.95	7.19	7.31	5.94	4.58	4.06	4.17	3.02
NUMBER OF MALES AGED 25-59										
0	19.3	20.86	20.71	21.98	23.49	24.38	25.83	27.29	28.13	29.27
1	68.4	66.01	65.9	65.52	62.53	61.56	61.98	61.15	60.21	59.38
>=2	12.3	13.14	13.39	12.5	13.99	14.06	12.19	11.56	11.67	11.35
NUMBER OF FEMALES AGED 25-59										
0	11.56	12.3	12.55	13.65	14.2	14.69	16.56	17.19	19.06	19.9
1	75.82	75.7	74.79	72.08	71.5	71.98	70.1	68.44	67.5	67.19
>=2	12.62	11.99	12.66	14.27	14.3	13.33	13.33	14.37	13.44	12.92
NUMBER OF ELDERS (59+)										
0	63.73	62.04	60.98	59.27	57.31	55.31	53.96	53.13	51.46	50.21
1	26.51	27.22	26.88	27.08	27.35	28.23	29.06	28.54	28.54	30.73
>=2	9.76	10.74	12.13	13.65	15.34	16.46	16.98	18.33	20	19.06

Table 6 Model Results - Odds Ratio Predicting "Not Enough Water""

HH Head			
Age	1.059***	1.057**	1.057**
Age squared	0.999***	0.999***	0.999***
Sex	1.134	1.105	1.100
No Education	1.039	1.228	1.240
Some Secondary	1.104	1.023	1.025
Finished Secondary	0.553	0.626	0.629
Vocational	1.194	1.247	1.239
Household Characteristics			
1 to 29% engaged in agriculture	1.519***	1.398***	1.390***
30 to 59% engaged in agriculture	1.736***	1.560***	1.558***
60+% engaged in agriculture	1.530***	1.337***	1.335***
Income quintile 2	0.735***	0.754***	0.755***
Income quintile 3	0.646***	0.673***	0.671***
Income quintile 4	0.597***	0.595***	0.593***
Income quintile 5	0.518***	0.566***	0.565***
Household Composition			
Number of males 15 to 24	1.010	1.024	1.022
Number of males 25 to 59	1.071	1.085	1.084
Number of females 15 to 24	1.044	1.056	1.055
Number of females 25 to 29	1.262***	1.230***	1.226***
Number of children 0 to 14	0.984	0.959	0.960
Number of elders 60+	1.229***	1.233***	1.227***
District and Village			
Below Average NDVI		2.024***	2.018***
Above Average NDVI		0.797***	0.795***
Bad for others in village		7.572***	7.548***
Share resources			0.949
BAAC member			1.090

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