Essays on Climatic Risks and Vulnerability-Reduction Strategies

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ABSTRACT

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This dissertation analyzes three different dimensions of climate risk: (i) impacts and responses to climate change in physical and biological systems; (ii) socio-economic consequences of climatic variability in human systems; and (iii) the design of formal insurance instruments to reduce socio-economic vulnerability to climatic risk, as adaptation strategies. Each part represents an independent study.

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Chapter 1

Introduction

My doctoral research is motivated by the need to better understand climatic risk and its environmental and socio-economic implications for sustainability. Climatic change and climatic variability can affect human beings both directly (e.g. increase in mortality associated to heat waves) and indirectly through their environment (e.g. reductions in agricultural yields). My work investigates the dynamic interaction between climate, men and the environment. Climate-induced environmental changes will have long-term socio-economics consequences on health, food security and water availability, especially in developing countries. Three examples: (i) changes in *natural ecosystems* associated with warmer temperatures are increasing the geographic habitat of vector diseases such as mosquitoes and rodents; (ii) increasing temperatures and weather extremes are expected to reduce productivity of *agricultural systems* (also referred to as *managed ecosystems*), which in turn will lead to malnutrition and micronutrient deficiencies; (iii) changes in *physical systems* such as the retreat of Himalayan glaciers threatens water supply and the lives of tens of millions of people (IPCC, 2007).

When I started my doctoral degree there were no studies linking global changes in physical and biological systems to anthropogenic climate change. Documenting and understanding this relationship was a necessary step toward an informed analysis of the socio-economic consequences of climatic risk, and eventually the design of adaptation strategies. These three areas of investigation also define the three parts that compose my dissertation: (i) impacts and responses to climate change in physical and biological systems; (ii) socio-economic consequences of climatic variability in human systems; and (iii) the design of formal insurance instruments to reduce socio-economic vulnerability to climatic risk, as adaptation strategies. Each part represents an independent study.

The first study formally links for the first time observed global changes in physical and biological systems to human induced climate change. By surveying a vast literature, my co-authors and I, demonstrated that changes in physical (i.e. cryosphere and hydrologic systems) and biological systems (i.e. terrestrial, marine and freshwater biological systems; agriculture; and forestry) are pervasive and that they lie predominantly in directions consistent with warming.

In order to perform this spatial meta-analysis I co-designed and built the Observed Climate Change Impacts Database, which includes about 80,000 data series from 577 peer-reviewed studies, and represents the first exercise in aggregating global data from different systems, both biological and physical; previous studies had looked mainly at single phenomena (e.g. plant physiological changes), or smaller areas.

We then analyzed the spatial correlation of temperature trends over the past 30 years with changes in physical and biological systems and showed that they are likely to be caused by anthropogenic climate change. We adopted the *joint-attribution approach*[1]. Joint attribution involves attribution of significant changes in a natural or managed system to regional temperature changes, and attribution of a significant fraction of the regional temperature change to human activities (Rosenzweig et al.

[1] Climate Change 2007: Working Group II: Impacts, Adaptation and Vulnerability, chapter 1.

(2007)).

The conclusions of this study, published in Nature in May 2008, and recipient of the NASA-GISS Best Publication Award 2008 – provide evidence that for the past 30 years, in regions affected by warming temperature trends, significant changes in physical and biological systems have been occurring on all continents and in most oceans.

Our analysis contributed also to the *IPCC 4th Assessment Report: Climate Change 2007*, recipient of the 2007 Nobel Peace Prize. In the first chapter in volume II of the 4th Assessment Report, evidence is assessed regarding observed changes (across systems and geographical regions) related to anthropogenic climate forcing. Also, using observations of the Observed Climate Change Impacts Database we developed the first global map of physical and biological impacts and changes[2] (IPCC 2007, WGII SPM and 1.4, figure 1.8).

Observed changes may vastly contribute to the study of adaptation and vulnerability. However, we found that there is a notable lack of geographical balance in the data and literature on observed changes in natural and managed systems, with a marked scarcity in the tropics and more generally in developing countries (IPCC 2007, Rosenzweig et al. 2008). This is unfortunate and ironic given that developing countries are expected to be particularly vulnerable in the face of climatic risk (IPCC, 2007). Risk management techniques requires information about not only impacts resulting from the most likely climate scenarios, but also impacts arising from lower-probability but higher-consequence events and the consequences of proposed

[2]Locations of significant changes in observations of physical systems (snow, ice and frozen ground; hydrology; coastal processes) and biological systems (terrestrial, marine and freshwater biological systems), are shown together with surface air temperature changes over the period 1970 to 2004 (from the GHCN-ERSST datatset). The data series met the following criteria: (1) ending in 1990 or later; (2) spanning a period of at least 20 years; (3) showing a significant change in either direction, as assessed by individual studies.

policies and measures (IPCC 2007, WG III 3.5, 3.6).

Weather shocks are already the self-reported most important risk faced by rural households[3] and extreme weather events (i.e. droughts, heat waves and floods) are projected to become more frequent in a warming climate (Allan, 2008). Due to limited socio-economic data series, there are few studies documenting observed effects of warming and weather extremes in subsistence agricultural systems, among rural populations, in developing countries. Policy needs a better understanding of the magnitude of impacts on rural households, their distribution across income groups, and the copying strategies available.

The second study in my dissertation explores vulnerability and adaptation to extreme weather events in subsistence agricultural systems using Mexican rural-household survey data. Mexico represents a useful case study having undergone diverse degrees of climatic variability across regions in the late 1990s; furthermore, in the same years the Mexican government collected an exceptional socio-economic longitudinal dataset from 506 villages and 24,000 households, in areas where 92% of households work in agriculture, and 90% of parcels are rainfed. I spatially joined gridded precipitation data with the longitudinal rural household survey dataset to investigate the vulnerability of rural households to different weather shocks (i.e. drought and extreme rainfall events). First, by using changes in post-shock consumption as a metric, I estimated the vulnerability of different income groups to persistent droughts and extreme rainfall; then, I exploited a randomized poverty reduction program (i.e. the public cash transfer program Progresa) to measure the benefits of this intervention in reducing vulnerability to weather shocks; and lastly, I studied migration decisions as a form of risk-management (with potentially extensive domestic and international

[3]In rural surveys from developing countries, respondents invariably cite weather extremes as the single most important risk faced by the household. Chapter 2 will describe these studies.

socio-political consequences).

My estimates indicate stronger post-shock contraction in non-food compared to non-food consumption, with extreme rainfall associated with stronger food contraction than droughts. These results seem to suggest intra-household reallocation of resources from food to non-food consumption, and adoption of adaptation strategies to persistent droughts. My estimates also show a dishomogeneous distribution of impacts across income groups, with poor households more vulnerable to extreme rainfall shock. This study rises important policy questions concerning the design and targeting of poverty reduction programs: my results show that Progresa interacted with weather shocks, reduced vulnerability of poor households but also increased domestic and international migration of family members. This study also highlights the importance of addressing risk and adaptation as a complement to poverty reduction programs.

Regional efforts are a necessity of effective risk management and adaptation planning, and require both national and supranational coordination. The African Union, for instance, is currently supporting efforts towards enhancing national and regional capacities to mitigate exposure to disaster risk though the institution of contingency funds and risk sharing strategies across regions. Innovative insurance instruments to spread weather risk across regions are particularly beneficial in developing countries where incomes are volatile due to the important role of agriculture, and where insurance and credit markets are still weak or inexistent.

In my last paper, I explore design options for weather-indexed insurance contracts that take into account regional climatic patters in Eastern-Central and Southern Africa. El Nino Southern Oscillation (ENSO) is an important component in modulating rainfall in this region. ENSO produces opposite climatic patterns: la Niña events are associated with dry climate in Eastern Africa and wet climate in Southern Africa; during El Niño years this precipitation dipole is inverted. I analyze payouts of weather-indexed insurance contract with respect to climate variability resulting from ENSO. In particular, I simulate and study the distribution of possible payouts using historical precipitation data. In this study, I argue that climate science (e.g. ENSO forecasts) could provide robust tools to design efficient weather-indexed insurance instruments at a regional scale; and I discuss opportunities for re-insurance at a sub-continental scale by pooling together contracts from regions with recurrent opposite climatic patterns.

Chapter 2

Attributing physical and biological impacts to anthropogenic climate change

Abstract.[1] Significant changes in physical and biological systems are occurring on all continents and in most oceans, with a concentration of available data in Europe and North America. Most of these changes are in the direction expected with warming temperature. Here we show that these changes in natural systems since at least 1970 are occurring in regions of observed temperature increases, and that these temperature increases at continental scales cannot be explained by natural climate variations alone. Given the conclusions from the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report that most of the observed increase in global average temperatures since the mid-twentieth century is very likely to be due to the observed increase in anthropogenic greenhouse gas concentrations, and furthermore that it is likely that there has been significant anthropogenic warming over the past 50 years averaged over each continent except Antarctica, we conclude that anthropogenic

[1]This study has been published: Rosenzweig, C., D. Karoly, M. Vicarelli, P. Neofotis, Q. Wu, G. Casassa, A. Menzel, T.L. Root, N. Estrella, B. Seguin, P. Tryjanowski, C. Liu, S. Rawlins, and A. Imeson. 2008. *Attributing physical and biological impacts to anthropogenic climate change.* Nature, 453, 353-357.

Our analysis also contributed to the IPCC Fourth Assessment Report Climate Change 2007: Working Group II, summary for policy makers and chapter 1.

climate change is having a significant impact on physical and biological systems globally and in some continents.

2.1 Introduction

The IPCC Working Group II Fourth Assessment Report found, with very high confidence, that observational evidence from all continents and most oceans shows that many natural systems are being affected by regional climate changes, particularly temperature increases (IPCC (2007), Rosenzweig et al. (2007)). The Working Group II further concluded that a global assessment of data since 1970 shows that anthropogenic warming is likely ($66 - 90\%$ probability of occurrence) to have had a discernible influence on many physical and biological systems. Here we expand this assessment with a larger database of observed changes and extend the attribution from the global to the continental scale using multiple statistical tests. We also consider the part that other driving forces, especially land-use change, might have played at the study locations.

The rest of the chapter is organized as follows: section 2 presents a short survey of observed responses to climate change in natural systems; section 3 introduces and discusses the joint attribution approach adopted in this study; section 4 describes the methodology used; section 5 presents our results; and section 6 concludes.

2.2 Survey of observed responses to climate change

Observed responses to climate change are found across a wide range of systems as well as regions. Changes related to regional warming have been documented primarily in terrestrial biological systems, the cryosphere and hydrologic systems; significant

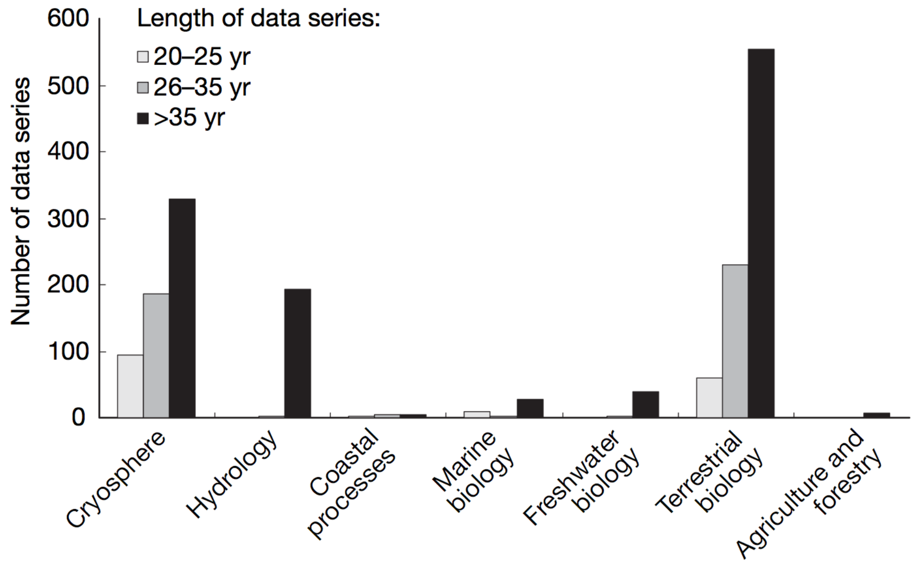

Figure 2.1: Data series of observed changes in physical and biological systems. Length of the data series and types of observed changes in physical and biological systems. COST725 data series of terrestrial biological changes ($\sim 28,000$ European phenological time series (Menzel et al. (2006)) were measured over 30 years (1971-2000; not displayed).

changes related to warming have also been studied in coastal processes, marine and freshwater biological systems, and agriculture and forestry (Fig. 2.1). In each category, many of the data series are over 35 years in length.

Responses in physical systems include shrinking glaciers in every continent (Dyugerov et al. (2005), Oerlemans (2005)), melting permafrost (Frauenfeld et al. (2004), Yoshikawa and Hinzman (2003)), shifts in the spring peak of river discharge associated with earlier snowmelt (Cayan et al. (2001) Mote et al. (2005)), lake and river warming with effects on thermal stratification, chemistry and freshwater organisms (O'Reilly et al. (2003), Sorvari et al. (2002), Daufresne et al. (2004)), and increases in coastal erosion (Beaulieu and Allard (2003), Forbes et al. (2004), Orviku et al. (2003)). In biological systems, changes include shifts in spring events (for example, leaf unfolding, blooming date, migration and time of reproduction), species distributions and community structure (Root et al. (2003), Parmesan and Yohe (2003), Menzel et al. (2006)). Additionally, studies have demonstrated changes in marine-ecosystem functioning and productivity, including shifts from cold-adapted to warm adapted communities, phenological changes and alterations in species interactions (Richardson and Schoeman (2004), Edwards and Richardson (2004), Beaugrand and Reid (2003), Atkinson et al. (2004)).

2.3 Detection and attribution in natural systems

Following the definition of attribution of observed changes in the climate system (Mitchell et al. (2001)), changes in physical and biological systems are attributed to regional climate change based on documented statistical analyses confirmed by process-level understanding in the interpretation of results. For example, a statistical association between poleward expansion of species ranges and warming temperatures is expected when temperatures exceed physiological thresholds. The observed changes in both climate and the natural system are demonstrated to be: unlikely to be entirely due to natural variability; consistent with the estimated responses of either physical or biological systems to a given regional climate change; and not consistent with alternative, plausible explanations of the observed change that exclude regional climate change.

Attribution of changes in natural systems to anthropogenic warming requires further analysis because the observed regional climate changes must be attributed to anthropogenic causes. Combining these two types of attribution, called "joint attribution" (Rosenzweig et al. (2007)), has lower statistical confidence than either of the individual attribution steps alone.

One approach to joint attribution, which uses what may be called an "end-to-end" method, has already been conducted in several studies of specific physical and biological systems. This approach involves linking climate models with process-based or statistical models to simulate changes in natural systems caused by different climate forcing factors, and comparing these directly with observed changes in natural systems. When temperature data from the HadCM3 global climate model were used to examine the likely cause for changes in the timing of spring events of Northern Hemisphere wild animals and plants, results show the strongest agreement when the modeled temperatures were derived from simulations incorporating anthropogenic forcings (Root et al. (2005)). Other similar studies have shown that the retreat of two glaciers in Switzerland and Norway cannot be explained by natural variability of climate and glacier mass balance (Reichert et al. (2002)), that observed global and Arctic patterns of changes in streamflow are consistent with the response to anthropogenic climate change (Milly et al. (2005), Wu et al. (2005)), and that the observed increase in the area of forests burned in Canada over the last four decades is consistent with the response caused by anthropogenic climate change (Gillet et al. (2004)).

Here we conduct a joint attribution study across multiple physical and biological systems at both the global and the continental scale. We demonstrate statistical consistency of observed changes (which are very unlikely to be caused by natural internal variability of the systems themselves or other driving forces) in natural systems with warming and conduct spatial analyses that show that the agreement between the patterns of observed significant changes in natural systems and temperature changes is very unlikely to be caused by the natural variability of the climate. Combined with the attribution of global and continental-scale warming to anthropogenic climate forcing demonstrated by IPCC Working Group I Fourth Assessment Report, this analysis provides strong support for joint attribution of observed impacts.

2.4 Methods

We developed a database of observed changes in natural systems from peer reviewed papers, demonstrating a statistically significant trend in change in either direction related to temperature and containing data for at least 20 years between 1970 and 2004. Observations in the studies were characterized as a "change consistent with warming" or a "change not consistent with warming". The databases of the observed significant changes in the natural systems were overlaid with two gridded observed temperature data sets and the spatial patterns of the observed system changes were compared with the observed temperature trends using two different pattern-comparison measures.

Database of observed changes. We developed a database of observations from peer-reviewed papers (primarily published since the IPCC Third Assessment Report (2001)), specifically documenting the data series in terms of system, region, longitude and latitude, dates and duration, statistical significance, type of impact, and whether or not land use was identified as a driving factor. Data for the system changes were taken from ~ 80 studies (of which ~ 75 are new since the Third Assessment Report) containing 29,500 data series. Studies were selected that demonstrate a statistically significant trend in change in either direction in systems related to temperature or to other climate change variables as described by the authors, and that contain data for at least 20 years between 1970 and 2004 (although study periods may extend earlier or later). Observations in the studies were characterized as a "change consistent with warming" or a "change not consistent with warming".

Spatial analysis. Databases of the observed significant changes in the natural systems and the regional temperature trends over the period 1970-2004 were overlaid in a geographical information system. For Europe, even though there were very large numbers of observed response data series in some cells, these were counted as single cells in the spatial analysis. Two different gridded observed temperature data sets were used: HadCRUT3 (Brohan et al. (2006)) and GHCN-ERSST (Smith and Reynolds (2005)), both of which were used in the IPCC Fourth Assessment Report. In each $5° \times 5°$ grid cell, the observed system responses were assessed as consistent with warming or not consistent with warming-based on a decision rule of 80% or more of data series consistent with warming within a cell-providing a binary pattern of 183 (HadCRUT3) and 203 (GHCN-ERSST) cells across the globe. There are fewer cells with temperature data in the HadCRUT3 data set because it does not use any infilling of data from adjacent cells, unlike GHCN-ERSST. All cells with observed temperature data are included from each of the data sets, irrespective of the sign of the temperature trend.

The spatial patterns of the observed system changes were compared with the observed temperature trends using two different pattern-comparison measures. To assess the significance of these observed measures of pattern agreement, global temperature trend data were obtained from long control simulations with seven different climate models from the WCRP CMIP3 multi-model database at PCMDI, to represent the range of 35-year temperature trends across the globe resulting from natural climate variations. The global temperature trend fields from the climate models represent the spatial coherence and decadal variability of natural internal temperature variations. Two different pattern-comparison measures were used: a binary pattern congruence (uncentred pattern correlation) between the gridded binary field of system responses consistent (or not consistent) with warming and the gridded field of positive (or negative) temperature trends; and a pattern congruence between the gridded binary field of system responses and the gridded field of standardized temperature trends (the 35-year temperature trends divided by the standard deviation of 35-year temperature trends caused by natural internal climate variations). For each of these measures, the observed values for the two different observed temperature-trend data sets were compared with the distributions obtained using temperature trends caused by natural internal climate variability, as represented by the climate models. Significant attribution was assigned when both spatial statistics methods and both temperature data sets showed significant results.

2.5 Results

2.5.1 Consistency with warming

Based on a database of documented responses in physical and biological systems from 1970 to 2004, temperature-related changes have been observed in all continents. Each documented response is a "statistically significant" signal that is beyond the natural internal variability of those systems. The largest numbers of entries in the database are for Europe and North America, followed by North Central Asia (Fig. 2.2). Sparse evidence of responses related to temperature changes exists in Latin America, Africa and Australia. Physical and biological systems in regions without data series may or may not be changing, but are not documented in peer-reviewed literature. Most (about 90% of the $> 29,500$ data series, $P \ll 0.001$) changes in these systems at the global scale have been in the direction expected as a response to warming. Ninety-five per cent of the 829 documented physical changes have been in directions consistent with warming, such as glacier wastage and an earlier spring peak of river discharge. For biological systems, 90% of the $\sim 28,800$ documented changes in plants and animals are responding consistently to temperature changes (mostly by means of earlier blooming, leaf unfolding and spring arrival). Warming in oceans, lakes and rivers is also affecting marine and freshwater biological systems (for example, changes in phenology, migration and community composition in algae, plankton and fish).

An evaluation of possible publication bias has been undertaken using comprehensive phenological network data in Europe (Menzel et al. (2006)), in which a systematic analysis of all available records (for example, leafing and flowering) documented the percentages of data series that are not changing and of significant changes in both directions (for example, in spring, in 66% there is no significant change, in 31% the onset dates are significantly advanced, and in 3% the onset dates are significantly delayed)(Menzel et al. (2006)). The percentage of data series with significant changes consistent with warming found in Europe ($\sim 90\%$) is close to that found in North America and Asia, providing an indication that the database may represent an unbiased sample of changes in both directions in those continents.

2.5.2 Spatial analyses at global and continental scales

The IPCC Working Group I Fourth Assessment Report concluded that most of the observed increase in global average temperatures since the mid-twentieth century is very likely ($> 90\%$ probability of occurrence) to be due to the observed increase in anthropogenic greenhouse gas concentrations (IPCC, Climate Change 2007). It is very likely that the observed warming patterns cannot be explained by changes in natural external forcing factors, such as changes in solar irradiance or volcanic aerosols; the latter is likely to have had a cooling influence during this period.

At the global scale, agreement between the pattern of observed changes in physical and biological systems and the pattern of observed temperature change holds for two different gridded temperature data sets and two different pattern-comparison methods, and is exceptionally unlikely ($P \ll 0.01$) to be explained by natural internal climate variability or natural variability of the systems; the latter is determined in

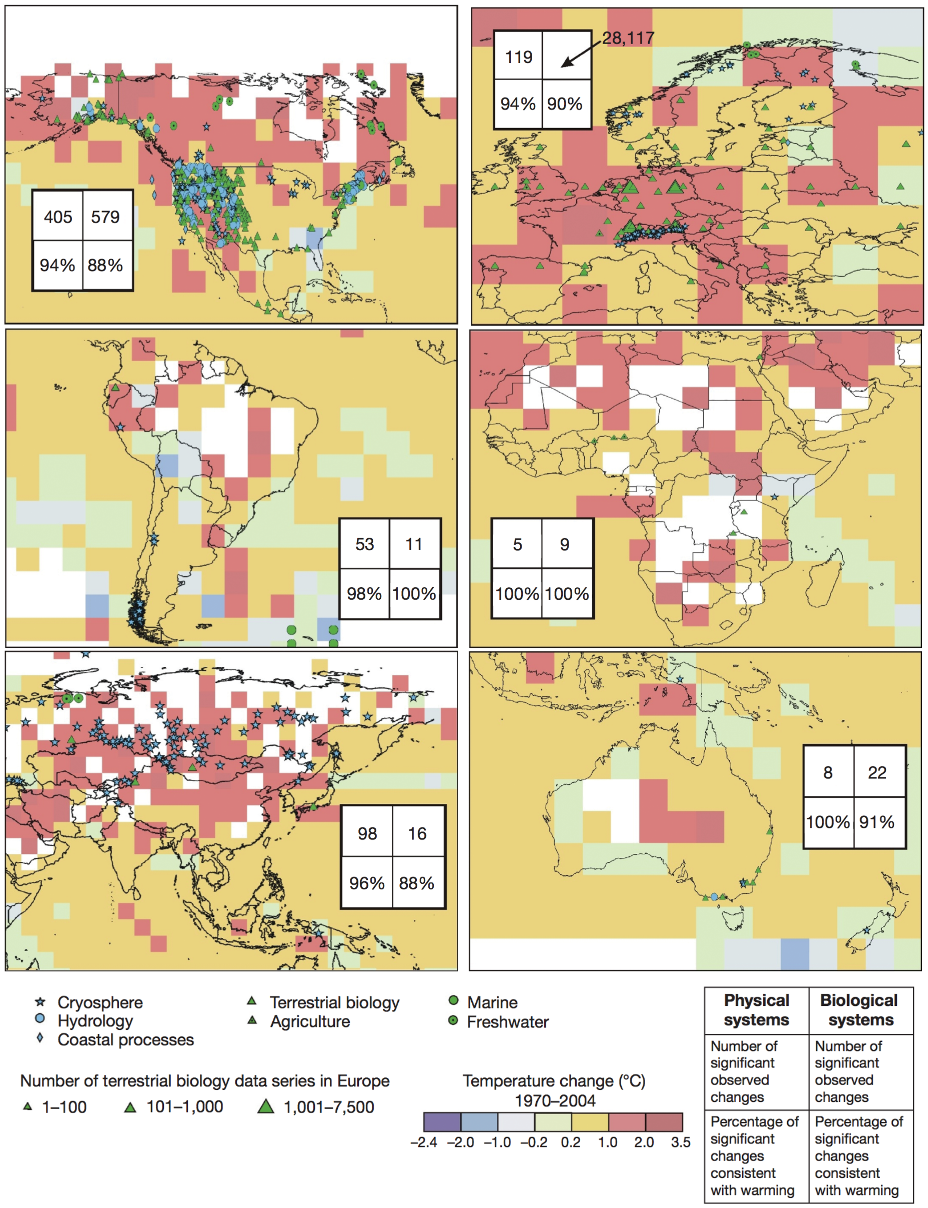

Figure 2.2: Location and consistency of observed changes with warming. Locations of significant changes in physical systems (snow, ice and frozen ground as well as hydrology and coastal processes) and biological systems (terrestrial, marine and freshwater biological systems), and linear trends of surface air temperature (HadCRUT3; ref. 35) between 1970 and 2004. Regions are based on data in Giorgi (2002) and Stott (2003). White areas do not contain sufficient climate data to estimate a trend. Note that there are overlapping symbols in some locations; Africa includes parts of the Middle East.

the individual studies (Fig. 2.3). The spatial coherence of temperature trends across the globe is taken into account in these pattern comparisons using more than 3,000 years of climate model simulation data. The prevalence of observed statistically significant changes in physical and biological systems in expected directions consistent with anthropogenic warming in every continent and in most oceans means that anthropogenic climate change is having a discernible effect on physical and biological systems at the global scale.

For the first time, IPCC Working Group I Fourth Assessment Report extended its attribution of temperature trends to the continental scale, concluding that it is likely that there has been significant anthropogenic warming over the past 50 years averaged over each continent except Antarctica (Hegerl et al. (2007)). Similarly, a discernible anthropogenic influence is found in changes in natural systems in some continents where there is sufficient spatial coverage of responses in natural systems, including Asia and North America, and marginally in Europe. In these continents, there is a much greater probability of finding coincident significant warming and observed responses in the expected direction. Despite the presence of strong climate variability related to the North Atlantic Oscillation in Europe as well as its relatively small size, which makes it harder to distinguish signal from noise (Hegerl et al. (2007)), the plethora of evidence allows a signal to be detected, primarily in biological systems. The statistical agreement between the locations and directions of observed significant changes in natural systems and observed significant warming across Asia and North America ($P < 0.05$) and across Europe ($P \sim 0.1$) is very unlikely to be due to natural variability alone Fig. 2.3. Responses not consistent with warming observed in $5° \times 5°$ grid cells with warming temperature may be due to those systems responding to seasonal rather than recorded annual changes or to local cooling not represented in average cell temperatures; biological variation across species may also have a role

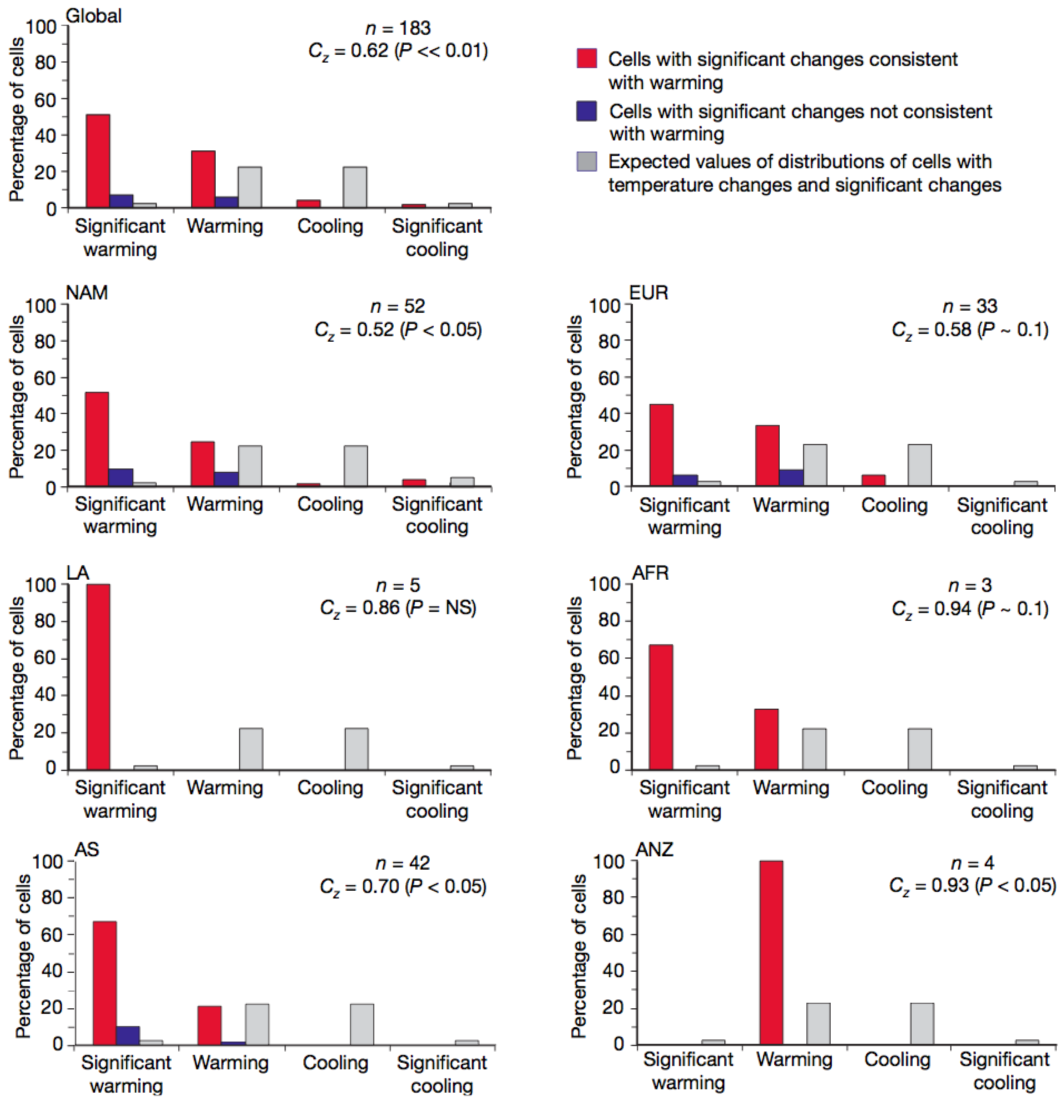

Figure 2.3: Distribution of cells with temperature changes and significant observed changes. Expected and observed distributions of cells with significant responses consistent with warming and distributions of cells with significant responses not consistent with warming for $5° \times 5°$ grid cells of temperature change between 1970 and 2004 (HadCRUT3). The global total includes polar regions and marine systems. Shown is the number of cells (n) with observed impacts and temperature data, the pattern congruence between locations of significant responses and standardized temperature trends (C_z), and the probability (P) that pattern agreement could be explained by natural internal variability of temperature fields. Abbreviations: AFR, Africa; ANZ, Australia and New Zealand; AS, Asia; EUR, Europe; LA, Latin America; NAM, North America; NS, not significant.

(for example, late flowering species tend to be less affected by warming than earlier flowering ones). For the other continents, the sparse coverage of observed response studies makes it difficult to separate the observed responses related to anthropogenic temperature rise from those possibly caused by large-scale natural climate variations.

2.6 Discussion and conclusions

The wide variety of observed responses to regional climate trends in expected directions combined with the attribution of climate trends to anthropogenic causes at both global and continental scales (IPCC Climate Change 2007) demonstrates that anthropogenic climate change is already having a significant impact on multiple systems globally and in some continents. Most observed system changes are found in the cryosphere and in terrestrial biological systems and are consistent with the functional understanding and modelled predictions of climate change impacts. The far fewer data series in Africa, Australia and Latin America are closely co-located with warming, but these cannot yet be attributed to anthropogenic climate forcing.

The issues of other climate and non-climate driving forces are important. In considering other drivers of change for phenology, much of the evidence in plants comes from changes observed in the spring. Even though day length can have a modulating effect on spring phenology depending on the plant species, it is not a factor in these studies because species remain *in situ* for the length of the time series, during which day length has not changed. There is also the possibility that increasing CO2 is directly influencing plant phenology; however, experimental results show no consistent direction of response (that is, an advance or delay) (Ashoff et al. (2006)). Concerning trees, older trees tend to unfold leaves in spring later than younger ones, so with longer time series on one specific object, the onset dates should become later with time owing to ageing, not earlier as observed owing to warming. Finally, some of the plant data, especially in Europe, come from phenological gardens that have been protected from the direct effects of land-use change for decades.

Land-use change, management practices, pollution and human demography shifts are all-along with climate-drivers of environmental change. Explicit consideration of these factors in observed change studies strengthens the robustness of the conclusions. To determine the role of other driving forces in the data series used in this analysis, we assessed the likelihood of their having a direct effect on the observed system Out of the $\sim 29,500$ data series documented in ~ 80 studies included in the database, effects documented in only 3 studies (9 data series in 4 cells) were likely to have been caused by a driving force other than climate change (for example, habitat destruction, pollution or fishery by-catch disposal). Removing these data series from the statistical analyses does not change the results significantly.

Land-use change can affect physical and biological systems indirectly through its effects on climate. Yet, for recent climate trends on a global scale, the effect of land-use change is small (Hegerl et al. (2007)). In addition, because these effects may result in warming in some regions and cooling in others (for example, agricultural expansion tends to warm the Amazon and cool the mid-latitudes) (Bounoua et al. (2002), Brohan et al. (2006)), they are very unlikely to explain the coherent responses that have been found across the diverse range of systems and across the continental and global scales considered Cooling in temperate regions occurs because the clearing of forests for agriculture may increase albedo during periods of snow cover, although recent afforestation may be dampening this effect.

Documentation of observed changes in physical and biological systems in tropical and subtropical regions is still sparse. These areas include Africa, South America, Australia, Southeast Asia, the Indian Ocean and some regions of the Pacific. One reason for this lack of documentation might be that some of these areas do not have pronounced temperature seasons, making events such as the advance of spring phenology less relevant. Other possible reasons for this imbalance are a lack of data and published studies, lag effects in responses, and resilience in systems. Improved observation networks are urgently needed to enhance data sets and to document sensitivity of physical and biological systems to warming in tropical and subtropical regions, where many developing countries are located.

Author Contributions C.R., D.K., G.C., A.M., T.L.R., B.S., **M.V** and P.N.. conceived the analytical framework; **M.V.** designed the database; P.N., **M.V.**, A.M. and N.E. constructed the database; **M.V.**, D.K. and Q.W. performed the statistical analyses; **M.V.** developed maps and figures; G.C., A.M., T.L.R., P.T., B.S., C.L. and S.R. provided expertise in observed changes in physical and biological systems; and P.N., A.M., C.R. and A.I. analysed other driving forces.

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Chapter 3

Socio-economic impacts of weather extremes in rural Mexico

Abstract Weather shocks are the self-reported most important risk faced by rural households in developing countries. Policy needs a better understanding of magnitude and distribution of impacts across income groups and the copying strategies adopted by rural households. This study estimates the vulnerability of different income groups to persistent droughts and extreme rainfall by using changes in post-shock consumption as a metric. By joining precipitation data from Mexico with rural household survey data I find higher vulnerability to severe rainfall for poor households than high income households, with a reduction in food consumption of about 18% versus 12.8%. My data allows me to use a randomized public cash transfer program to measure the benefits of this intervention in reducing vulnerability. My estimates indicate that after severe rainfall treated households were able to partially smooth their food consumption by 5%. Migration is a risk-management strategy frequently adopted in rainfed agricultural regions in response to weather extremes. I find that public cash transfers increased the domestic and international migration of members of households hit by weather shocks. These findings about Mexico are significant from a global perspective given that extreme weather events are projected to become more frequent in a warming climate and many subtropical and semi-arid tropical regions

will experience decreasing agricultural yields associated to climate change.

3.1 Introduction

"Most of the people in the world are poor, so if we knew the economics of being poor we would know much of the economics that really matters. Most of the world's poor people earn their living from agriculture, so if we knew the economics of agriculture we would know much of the economics of being poor." (Theodore Shultz, acceptance speech for the 1979 Nobel Memorial Prize in Economics).

Recent research suggest that the picture depicted by Schultz more than 30 years ago has not changed: most of the poor still live in rural areas, a large share of them depend on agriculture for a living, and the incidence of poverty tends to be higher in agricultural and rural populations than elsewhere (World Bank, 2008; Ravallion and Chen, 2007). Moreover, the recent pace of urbanization and current forecasts for urban population growth imply that a majority of the world's poor will still live in rural areas for many decades to come (Ravallion and Chen, 2007).

Vulnerability to income-shocks (e.g, illness, famine, war, drought) is an important dimension of poverty. In rural-household surveys in developing countries, respondents invariably cite weather extremes as the single most important risk[1]. Vulnerability to weather shocks has vast implications[2], it affects food security and growth, and it is likely to worsen in the 21^{st} century; climate models predict that extreme weather events will become more frequent due to anthropogenic climate change.

Weather shocks can differ in duration (e.g. persistent droughts versus sudden

[1]PROGRESA dataset from Mexico (1998-1999); Ethiopian Rural Household Survey (1999-2004), Dercon and Krishnan, (2000); an Indian survey described in Gine Townsend and Vickery, (2008)

[2]Considering also that rainfed agriculture is practiced in about 80% of the world total agricultural area and generates 62% of the world's staple food (FAOSTAT, 2008).

floods) and intensity. In order to optimize the targeting and efficiency of risk management and poverty reduction interventions, policy needs a better understanding of the magnitude and distribution of impacts across different income groups, as well as the copying strategies available to rural households.

By spatially joining physical precipitation data with household survey data, this paper studies the vulnerability to weather shocks in different income groups. I focus on two different weather shocks, persistent droughts and extreme rainfall. Post-shock consumption is used as a metric for vulnerability. This paper also investigates the impact of weather shocks on migration of family members, a common risk management strategy that may generate important socio-economic consequences both nationally and internationally.

Much of the literature investigating the role of income shocks on household welfare has focused on three main aspects: the informal insurance mechanisms available at the households and village level to smooth post-shock consumption; the magnitude of short-term changes in household food and non-food consumption in response to uninsured shocks; and the long-term impacts on socioeconomic welfare.

In the wake of Townsend's (1994) seminal paper, much empirical research has focused on testing informal insurance and *perfect risk-sharing* in rural villages[3]. In poor rural areas, insurance and credit markets are weak or missing and household insure their income and consumption using informal strategies. Results have failed to find perfect consumption smoothing in the face of idiosyncratic (i.e. household-level) shocks but did find evidence of *partial risk-sharing* (e.g. private food and monetary

[3]If communities perfectly pool their incomes to share risks, the consumption level of a given household should be only a function of the total community income. The household own's income should then not affect consumption patterns, and all idiosyncratic (i.e. household-level) shocks should be eliminated (Morduch, 1999).

transfers)[4].

Empirical results indicate that when gifts and private transfers are not sufficient to absorb income shocks, households adopt a variety of informal insurance mechanisms. Most of these mechanisms are costly adjustments for the household; they include dissaving (e.g. Paxson, (1992)), depleting assets (e.g. Fafchamps et al. (1998); Kazianga and Udry, (2006)), and child labor with consequent reduction in school attendance (Jacoby and Skoufias, (1997))[5].

Evidence suggests that, even despite these adjustments, rural households remain significantly underinsured in the face of a variety of idiosyncratic and covariate (i.e. village-level) shocks. Skoufias and Quisumbing (2005) and Dercon et al. (2005) found a significant short-term contraction in food and non-food consumption generated by a variety of underinsured income shocks that include health risks (e.g. illness, malnutrition, famine), social risks (e.g. crime), economic risks (e.g unemployment, financial crisis) and natural risks (e.g. drought, pests)[6].

Exposure to uninsured risk may also have long-term welfare impacts. There is a growing body of literature showing the long-term impacts of income shocks on human capital formation, namely health status and educational attainments. Two main groups of studies have emerged: one focusing on the impacts of armed conflicts (Alderman, Hoddinot and Kinsey (2006) for Zimbabwe; Akresh and Vewimp (2006) for Rwanda; Bundervoet et al (2009) for Burundi; Miguel and Roland (2010) for Vietnam), the other group on rainfall shocks. Using household data from rural Ethiopia,

[4]Townsend (1995) and Murdoch (1995, 1999) review the literature testing perfect risk-sharing.

[5]Murdoch (1995, 1999) and Dercon (2004) provided detailed reviews of income and consumption smoothing mechanisms.

[6]Skoufias and Quisumbing (2005) synthesize results from studies in five countries describing changes in food and non-food consumption associated to income oscillations (in Mexico), self-reported health shocks (in Mali, Bangladesh and Ethiopia), loss of livestock (theft or death) and wage and unemployment shocks (in Russia). Dercon et al. (2005) investigate changes in household consumption caused by a variety of self-reported shocks in rural Ethiopia (drought, pests, crime, illness or death of household members).

Dercon (2004) finds that rainfall shocks in 1984-5 had a a persistent effect on households consumption growth in the 1990s. Hoddinot and Kinsey (2001) and Alderman, Hoddinott, and Kinsey (2006) show that droughts are causally related to reduced human capital formation in Zimbabwe. Using Indonesian data for females, Maccini and Yang (2009) find similar results; their estimates indicate that local rainfall variations around the time of birth significantly affect schooling, health and socio-economic status in adulthood.

This paper contributes to the literature studying the magnitude of short-term changes in household consumption in response to uninsured weather shocks. I will measure changes in food and non-food consumption in different income groups, after different weather shocks. The methodology used is new: I spatially join gridded precipitation data with longitudinal household data collected to evaluate a randomized poverty reduction intervention (i.e. the conditional cash transfer Progresa). This dataset simulates a natural experiment and allows me to also investigate the effects of the interaction between a randomized government program and weather shocks. My results will have bearing also on the analysis of impacts of future climate change. Climatic factors may play an increasingly important role in the lives of the rural poor especially in the subtropics (e.g. Central America). There is a broad consensus among climate models that the subtropics will dry in the 21st century and that the transition toward a more arid climate is already under way (Seager et al. 2007). Moreover, climate models suggest that extreme precipitation will become more common in a warmer climate (Allan, 2008). The scenario emerging for the subtropics is therefore a more arid climate punctuated by more frequent rainfall extremes[7].

Mexico represents a useful case study, having undergone diverse degrees of cli-

[7]Furthermore, the amplification of rainfall extremes currently observed is found to be larger than predicted by models, implying that projections of future changes in rainfall extremes in response to global warming might be underestimated (Allan, 2008).

matic variability (e.g. extreme rainfall and droughts) across regions in the late 1990s. I use precipitation data from 1998 and 1999, two years of strong weather variability induced by a combination of three climatic phenomena: the 1994-2004 decadal drought called *Mexican 21-st century drought* and two cyclical events, the 1997-8 El Niño (the strongest El Niño event of the past century) and the 1999 La Niña. I join precipitation data with rural household survey data from 506 villages and about 24,000 households. About 92% of households work in agriculture, and 95% of parcels owned or used for agriculture are rainfed. I use variations in post-shock food and non-food consumption as a metric for vulnerability. My analyses lead to the following findings. First, as expected, household total consumption was negatively affected by both acute rainfall and persistent droughts, with contractions of about 10% and 17% respectively. Second, households seemed to trade off non-food for food consumption; non-food consumption was reduced by about 25-30% after weather shocks while the effect on food consumption was smaller (5-13%). Third, food-consumption seemed more severely affected by acute rainfall (-13%) then persistent droughts (-5%). A possible explanation, that will be further explored in this paper, is the ability to adapt to persistent conditions. Fifth, the impact of weather shocks differ by income groups, and low-income households seem more vulnerable than high-income households to intense rains: in absence of treatment, poor households are associated to an 18% contraction (vs 13% for non-eligible households), which is larger in both absolute and relative terms than the contraction experienced by non-eligible households.

Recent empirical work has demonstrated the many benefits of conditional cash transfers on various socio-economic welfare outcomes such as health, education and poverty (e.g. Skoufias et al. (2001), Handa and Davis (2006)). I exploit the Progresa randomized experiment that provided cash transfers to households in rural Mexico starting in 1998, and I use a longitudinal dataset over two years to measure the benefits of the public cash transfer in mitigating vulnerability to shocks. To my knowledge, this is the first study that combines historical precipitation data with a randomized public intervention to measure its ability in mitigating vulnerability to weather shocks. The Progresa transfers were randomized at the village level, in treated villages only eligible[8] households were entitled to the benefits. My estimates lead to the following conclusions. First, the monthly transfers (equivalent to about 20% of low income households' monthly total consumption) reduced vulnerability of poor households particularly in case of acute rains by partially smoothing, by about 5%, the contraction in food consumption. The transfer did not help smooth non-food consumption. Second, I use the randomized public cash transfer program to also test for the presence of risk sharing arrangements at the village level. I found two positive spillover effects of Progresa. First, immediately after weather shocks, Progresa had a mitigating effect; households receiving the cash transfer were less vulnerable to extreme rainfall events (unexpected/acute shocks) and able to partially smooth post-shock consumption ($\sim +5\%$). Second, in treated villages, one year after the beginning of the intervention (in 1999), Progresa benefits had spread to non-eligible households ($\sim +11 - 12\%$ in food consumption) except for villages that experienced a drought in 1998. This seem to indicate that inter-household transfers and partial risk sharing at the village level are less likely in correspondence to persistent shocks (drought), and more likely when acute shock (extreme rainfall events) or no shocks occur.

A major consequence of large weather shocks is migration, Feng et al. (2010) and Pugatch and Yang (2010) find increased migratory movements from Mexican

[8]Eligibility was determined by the value of a poverty index that incorporate income and assets levels (Skoufias, 2001).

states hit by droughts. Migration can be an important risk management strategy for households but unmanaged and unexpected climate-related domestic or international migration can represent a major socio-political concern. Poverty reduction interventions in rural areas may also affect migration. Angelucci (2004) shows that the Progresa cash transfer program is associated with an increase in international migration, and the possible explanation is that the grant may loosen financial constraints. This paper complements Angelucci's study by investigating the effect of the interaction between weather shocks and the randomized cash transfer on the decision to migrate for different income groups. Droughts and acute rains increase by respectively 2 and 3 percentage points the likelihood that a household member migrates abroad or to a different state in search of work. My estimates confirm Angelucci's results, the cash transfer seems to have increased mobility from treated villages in general, and especially for women from richer households after droughts. My estimates also show that after extreme rainfall shocks (acute shocks that may compromise the harvest at the end of the agricultural season), women's mobility increased by 2 percentage points. Women emerge as possible temporary migrants in times of unexpected financial needs.

The remainder of this paper is organized as follows. The next section presents the Progresa program and descriptive statistics. Section 3 provides an overview of the hydro-climatic conditions in Central Mexico during the 1990s. Section 4 outlines the empirical methodology, Section 5 presents the results, and Section 6 concludes.

3.2 Description of the Progresa program

This section presents a brief history and overview of the functioning of the Conditional Cash Transfer (CCT) program Progresa. It draws extensively from Skoufias, (2005)[9].

In 1997, the Mexican government started the first nationwide controlled randomized anti-poverty program. Progresa, now called Oportunitades, is a Conditional Cash Transfer (CCT) program to promote human capital development: families received transfers conditional on their participation in health programs and on children's school attendance. Over the last ten years, CCT programs have come to dominate the social protection sector in Latin America and the Caribbean, in part also because of Progresa's success.

The Progresa pilot phase (1998-2000) included a robust monitoring system to conduct independent post-intervention impact evaluations in 506 villages located in 7 Mexican states: San Luis Potosi, Veracruz, Queretaro, Hidalgo, Puebla, Michoacan de Ocampo and Guerrero. Progresa's monthly CCTs started in May 1998 and corresponded to about 20% of households' monthly pre-intervention consumption. The program design included 5 post-intervention socio-economic household evaluation surveys (called Encuesta de Evaluacion de los Hogares or ENCEL), aimed at assessing the program's direct and indirect impacts. The surveys were carried out on November 1998, March and November 1999, and March and November 2000. In December 1999, all households in the control group started receiving the transfers.

The 24,000 households in the Progresa dataset fall in four different categories with respect to the transfer program: in 320 locations there are households that received the CCT and in the 186 control villages nobody received the benefits; however, in both treatment and control villages there are about 20% of households that were not eligible for the CCT.

[9] Skoufias (2005) provides detailed discussion of Progresa, the evaluation design and the estimated impacts of the program.

Because of its robust impact evaluation design, Progresa's direct and indirect impacts have been widely investigated. All primary indicators of direct impacts (e.g. school enrollment, preventive health check-ups for growth monitoring and vaccinations, pre-natal care, food availability and nutritional status) on beneficiary households compared with control households have shown significant increases in the expected direction (Behrman and Hoddinott, (2005); Skoufias, (2001); Hoddinott and Skoufias, (2004); Handa and Davis, (2006)). Progresa seems also to have produced positive spillover effects on non-beneficiary households (Handa et al., (2001)).

Several indirect significant impacts have also been documented such as: improvements in women's status and women's empowerment in intra-household decision-making (Adato et al., (2000)); and increase in the value of consumption (per person per month)[10] among treatment households by approximately 14.53% (Hoddinott et al., (2000)). Recent studies have focused on the role of networks (Angelucci et al. 2009 and 2010). Angelucci et al. (2010) find that Progresa only raises secondary enrollment among households that are embedded in a family network. Eligible but isolated households do not respond. Their study suggests that the mechanism through which the extended family influences household schooling choices is the redistribution of resources within the family network from eligibles that receive de facto unconditional cash transfers from Progresa, towards eligibles on the margin of enrolling children into secondary school.

3.2.1 Socio-Economic Data and Descriptive Statistics

Data used in this paper are drawn from the November 1998 (ENCEL98O) and November 1999 (ENCEL99N) surveys where comparable consumption information across

[10] This increase in value of consumption is concentrated mainly among two food groups: fruits and vegetables, and animal products.

rounds was collected. All the variables used in this empirical analysis are available at the household level. The main socio-economic variables used include two binary variables indicating eligibility to receive treatment E, and treatment T; and three continuous consumption variables: total consumption, food consumed, non-food expenditures. As explained above eligibility was determined by the value of a poverty index that incorporate income and assets levels (Skoufias, 2001). Villages are randomly selected for treatment ($T = 1$). Within treated villages only eligible households ($E = 1$) actually receive the cash transfer. For treated households $E * T = 1$.

The value of food consumed was calculated including both food produced and purchased; the variable food consumption is the sum of the value of consumption on fruits and vegetables, cereals and grains, meats and animal products, and industrial foods (e.g. sugar and beverages). Food consumption is expressed in pesos per month and is divided by the value of *adult equivalents* for each household[11]. Non-food expenditures do not include durable goods (e.g. appliances, motor vehicles etc.) and other luxury goods; and are expressed as pesos per capita, per month. Both food and non-food expenditures are expressed in October 1998 prices.[12]

Other variables included in this study are binary variables for self-reported losses such as loss of harvest, soil damage (thus, unsuitable for cultivation), loss of animals. Table 3.1 provides summary statistics for the main variables.

[11]The formula I used to calculate the parameter *Adult Equivalent* for each household is available in Deaton (2002): $AE = (adults + (\alpha * kids))^{\theta}$, where *adults* indicates the number of individuals of age above 10 year-old in the household; the variable *kids* indicates the number of children of age below 10 year-old in the household; $\alpha = 0.3$, and $\theta = 0.9$.

[12]For more details on the constructions of the consumption variables see the report by Hoddinott et al. (2000).

3.3 Hydro-climatic conditions in central Mexico

Climatic factors, namely drying trends and weather extremes, are expected to play increasingly important role in the lives of the rural poor, especially in the subtropics (e.g. Central America) (Seager et al., 2007; Allan, 2008). Mexico represents a useful case study: its agricultural production is mainly rainfed, and in the late 1990s, Mexico has undergone diverse degrees of climate variability (e.g. extreme rainfall and droughts) across regions.

In the late 90s rainfed agriculture accounted for about 75% of Mexican cultivated land, with irrigation concentrated in the remaining 25% (CONABIO, 1998)[13]. Rainfed agriculture dominates in the mountainous regions associated to the Progresa intervention (Central Mexico). In the socio-economic dataset used in this study about 92% of households work in agriculture, and 95% of parcels owned or used for agriculture are rainfed.

In this study, I use precipitation data from 1998 and 1999, two years of extreme precipitation events induced by a combination of three climatic phenomena: the 1994-2004 decadal drought and two cyclical events, the 1997-8 El Niño (the strongest El Niño event of the past century), and the 1999 La Niña.

In this section: first, I will provide a brief overview of the Central Mexican hydroclimate; second, I will describe the anomalous weather conditions observed during the 1990s; and third, I will present descriptive statistics for lages under exam.

The Mexican seasonal cycle of rainfall is affected by the combination of unique geographic conditions: latitudinal orientation, proximity to major bodies of water and complex topography.[14] These geographic features contribute to create diverse

[13] 93.8% of indigenous ejido (government land) and community lands were not non-irrigated (CONABIO, 1998)

[14] Mexico is a narrow strip of land extending in the north-south direction between two oceans: the

local climates within the region: from semi-arid climates in the North to tropical climates in the South. Most of the Progresa villages under examination are located in Central Mexico in the Sierra Nevada, between 25 and 17 degrees North. Maize is the primary crop in more than 90% of the villages in the Progresa dataset.

The annual cycle of precipitation in Central Mexico exhibits a bimodal distribution: the rainy season starts in late May, early June, and lasts through October; the dry season starts at the end of October until the following April (Curtis, (2002)). Rainy season and main agricultural season coincide; the planting phase starts in April-May and farmers harvest in September-November. In this region, called the *maize belt* of Mexico, precipitation maxima occur during May-June and September-October. The rainy season is characterized by a relative minimum during July-August, known as the midsummer drought (MSD), Canicula or Veranillo (Magaña et al., (1999); Curtis, (2002); Curtis and Gamble (2008).[15] The timing of the MSD coincides with the phase in the maize agricultural cycle that is the most sensitive to moisture (i.e. development phase). This means that a stronger than usual MSD can compromise the entire harvest.[16]

Dry episodes are not rare events. Short-term summer droughts and severe multi-decadal droughts with vastly negative socio-economic implications punctuate Mexican history (Peña and Douglas (2002)). Pavia et al. (2006) and Seager et al. (2007) have studied the variability of Mexican hydroclimate, with special attention to persistent

Pacific Ocean to the east, and to the west the Caribbean Sea, Gulf of Mexico and Atlantic Ocean. The Mexican topography results from the intersection of four mountain ranges. The territory is crossed meridionally by the Sierra Madre Oriental and the Sierra Madre Occidental; and longitudinally by the Sierra Nevada (also known as Trans-Mexican Volcanic Belt) in the central part of the country, and the Sierra Madre del Sur in the south.

[15] A bimodal precipitation structure is observed in other parts of the globe but never at these latitudes. The MSD is, therefore, a unique feature of the annual cycle of precipitations over Mexico and Central America.

[16] The region where the most dramatic changes in precipitation occur corresponds to the western coast of Mexico, while on the Atlantic side of the Mexican central mountain ranges the MSD signal is the weakest, confirming the crucial role of orographic structures (Magaña, (1999).

droughts; their results suggest that drought occurrence is caused by a strong natural atmosphere-ocean variability associated with El Niño Southern Oscillation (ENSO) events. In Central America, El Niño is historically associated with lower than average rains between April and November, which coincides with the main growing season in Mexico.

In the mid 1990s Mexico experienced a severe drought that continued through the first few years of the current century, known as the *21-st Century Drought* (Staehle, 2010). The central part of Mexico (that includes the Progresa villages) was exposed, more or less intensely, to the dry signal all along the 1990s. The *Climate Report for 1998* published by the American Meteorological Society (Bell et al., (1999)) indicates that the period July 1997 through June 1998, was the driest in the historical record for Mexico dating back to 1945, with below-normal rainfall observed in every month except November 1997. During this period rainfall totals averaged 20%-60% of normal over much of the country. During March-June 1998 this dryness, in combination with prolonged periods of extreme heat, led to an intensification of drought conditions which culminated in widespread forest fires. The Mexican drought were also linked to the 1997-98 El Niño, the strongest El Niño event of the past century (Bell et al. (1999)).

Precipitation anomalies during the 1997-1999 main agricultural seasons are shown in figure 3.1. The 1997 El Niño drought was exceptional not only for its intensity but also for its timing and duration. The event manifested itself only in late June, with a two month delay with respect to historical El Niño episodes. The other unusual aspect of the drought was the continuation of substantially below-normal rainfall during December-January-February 1997-98 across most of the country, despite the continuation of strong El Niño conditions. Historically, above-normal winter rainfall is observed across central and northern Mexico during these episodes (Ropelewski and Halpert (1986)), which helps to alleviate the rainfall deficits that typically develop during the previous summer and fall (Bell et al. (1999)). Because of its abnormal persistence, the El Niño drought affected the summer harvests of both 1997 and 1998.

This paper studies variations in consumption measured in November 1998 and 1999, at the end of the main agricultural season. Early droughts in 1998 suggested the beginning of a new dry season but the outcome did not confirm this anticipation. A 2-year La Niña event suddenly started in the summer 1998. As a consequence, during the harvest season in both 1998 (September) and 1999 (October), some areas experienced unexpectedly intense rains and even floods (Figure 3.1 and 3.2). October 1999 rainfall were particularly devastating. Harvesting of the important spring/summer maize crop had just started when above-normal rainfall across the central plateau created flood conditions and damaged crops, particularly in the states of Puebla, Veracruz, Hidalgo, Tabasco and Chiapas.[17] Severe damages and casualties in Jalisco, Michoacan, Puebla, and Tabasco prompted the Government of Mexico to designate these states as zones of disaster (FAS-USDA, 1998). The Progresa dataset includes villages in the zones of disaster (i.e. Puebla, Michoacan) as well as in Veracruz and Hidalgo, two states were precipitation were extremely abundant.

[17]Along the east and west coastlines, grain growing fields were touched by the overflow from swollen riverbeds prevalent in states. In the central plateau the abundant precipitation damaged the crops as plants were moving from maturation into the drydown phase.

3.3.1 Hydro-climatic Data and Descriptive Statistics

In this paper I use monthly precipitation data available from the University of East Anglia Climate Research Unit (UEA CRU -TS2p1) (Mitchell, (2005)) to measure the presence of rainfall shocks in the region under analysis. The monthly series are available as interpolated gridded data with a spatial resolution of 0.5 x 0.5 degrees. I use the standardized precipitation anomaly as regressor to analyze the impact of weather shocks on consumption. The variable was constructed in three steps: first, I calculated the monthly climatology for each gridcell (i.e. average precipitation over 30 years, from 1961 to 1999); second, I estimated the monthly gridcell (pixel) anomaly by subtracting the climatology from the precipitation level for each month in 1998-1999; and third, I divided the anomaly by the standard deviation in each gridcell to obtain the standardized precipitation anomaly.

The 506 progresa villages are distributed over 67 gridcells (pixels). The number of villages per gridcell varies, from a minimum of 1 to a maximum of 35. Dry and wet spells were not uniform in the region under analysis. Some areas were hit only by droughts early in the growing season, others only by intense rains during the harvest season and some areas experience both phenomena. I created two binary variables: *drought* and *extreme rainfall*. *Drought* equals 1 when the average standardized precipitation anomaly in April-May is below the median(-0.35). *Extreme rainfall* equals 1 when the standardized precipitation anomaly in September or October is above 1. Table 3.2 presents the distribution of the two weather shocks in control vs treatment villages, the figures suggest that there were no significant differences.

3.4 Effect of Exogenous Income Shocks on Household Consumption.

3.4.1 Empirical Specification

The empirical analysis is based on investigating the relationship between weather shocks and household consumption. The analysis is structured in five parts: first, assessing the correspondence between gridded precipitation signals and household self-reported impacts/losses; second, investigating the relationship between weather shocks and household consumption; third, comparing the magnitude of consumption contractions in poor and non-poor households; fourth, exploring if Progresa benefits affected the consumption patterns of households facing adverse income shocks; and lastly testing if climatic shocks have protracted negative effect on consumption.

First, I try to assess whether and to what extent we can observe a correspondence between gridded precipitation signals and household self reported losses. I regress responses about losses for household h, in village v, in pixel p and time t (L_{hpt}) (e.g. loss of harvest, loss of land, loss of animals) on droughts (D_{pt}) and extreme rainfall(R_{pt}) in the previous 6 months, their interactions, a year-fixed effect (δ_t) and an error term (ε_{hvpt}):

$$L_{hvpt} = \alpha + \beta_1 D_{pt} + \beta_2 R_{pt} + \xi(D_{pt} * R_{pt}) + \delta_t + \varepsilon_{hvpt} \tag{3.1}$$

The estimation of equation (3.1) revealed that the coefficient of the interaction term ξ was not significant and did not affect the other coefficients, therefore subsequent models do not include the interaction. Equation (3.1) has been expanded to include additional independent variables: income group (E_{hvp}), residence in a treated village (T_{vp}) and all their interactions. E_{hvp} is a binary variable equal to 1 when household h is *eligible* for treatment. T_{vp} is again a binary variable equal to 1 if village v has been randomly selected for treatment. Hence, the interaction term $E_{hvp} * T_{vp}$ is equal to 1 for households that actually receiving treatment. Estimates are reported in table 3.3 and discussed in Section 4.2.

$$\begin{aligned} L_{hvpt} &= \alpha + \beta_1 D_{pt} + \beta_2 R_{pt} + \beta_3 E_{hvp} + \beta_4 T_{vp} + \phi_4 (E_{hvp} * T_{vp}) \\ &\quad + \gamma_1 (D_{pt} * E_{hvp}) + \gamma_2 (D_{pt} * T_{vp}) + \gamma_3 (D_{pt} * E_{hvp} * T_{vp}) \\ &\quad + \theta_1 (R_{pt} * E_{hvp}) + \theta_2 (R_{pt} * T_{vp}) + \theta_3 (R_{pt} * E_{hvp} * T_{vp}) \\ &\quad + \delta_t + \varepsilon_{hvpt} \end{aligned} \tag{3.2}$$

As a second step of my empirical analysis, I study the impact of adverse weather shocks on consumption using a variation of equations (3.1) and (3.2) where the dependent variable is the logarithm of consumption of household h, in village v, pixel p and year t. Consumption is measured at the end of the harvest season:

$$lnC_{hvpt} = \alpha + \beta_1 D_{pt} + \beta_2 R_{pt} + \delta_t + \varepsilon_{hvpt} \tag{3.3}$$

Equation (3.3) is further expanded into the model specification corresponding to equation (3.4) in order to compare the magnitude of consumption contractions in poor and non-poor households, and to explore if and how Progresa benefits affected the consumption patterns of households facing adverse income shocks:

$$
\begin{aligned}
lnC_{hvpt} &= \alpha + \beta_1 D_{pt} + \beta_2 R_{pt} + \beta_3 E_{hvp} + \beta_4 T_{vp} + \phi_4 (E_{hvp} * T_{vp}) \\
&+\gamma_1 (D_{pt} * E_{hvp}) + \gamma_2 (D_{pt} * T_{vp}) + \gamma_3 (D_{pt} * E_{hvp} * T_{vp}) \\
&+\theta_1 (R_{pt} * E_{hvp}) + \theta_2 (R_{pt} * T_{vp}) + \theta_3 (R_{pt} * E_{hvp} * T_{vp}) \\
&+\delta_t + \varepsilon_{hvpt}
\end{aligned} \tag{3.4}
$$

Lastly, climatic shocks that occurred in period $(t-1)$ are included as regressors to test if the shocks had a protracted negative effect on consumption across the two periods studied (1998 and 1999).

$$
\begin{aligned}
lnC_{hvpt} &= \alpha + \beta_3 E_{hvp} + \beta_4 T_{vp} + \phi_4 (E_{hvp} * T_{vp}) \\
&+\psi_0 D_{pt-1} + \vartheta_0 R_{pt-1} \\
&+\psi_1 (D_{pt-1} * E_{hvp}) + \psi_2 (D_{pt-1} * T_{vp}) + \psi_3 (D_{pt-1} * E_{hvp} * T_{vp}) \\
&+\vartheta_1 (R_{pt-1} * E_{hvp}) + \vartheta_2 (R_{pt-1} * T_{vp}) + \vartheta_3 (R_{pt-1} * E_{hvp} * T_{vp}) \\
&+\delta_t + \varepsilon_{hvpt}
\end{aligned} \tag{3.5}
$$

An estimation detail worth noting is that all standard errors are clustered by pixel to adjust for heteroskedasticity and within-pixel correlation over time.

3.5 Results

3.5.1 Consumption Patterns

Self-reported Agricultural Losses. The first step in my analysis has been to explore the relationship between self-reported losses and weather shocks. Although self-reported losses are a questionable measure of actual losses, this preliminary test allows us to map possible channels through which weather shocks might have affected household consumption. I expect weather shocks in 1998 and 1999 to have caused losses in harvest, cultivable land (i.e. damaged soil), animals and hardware. Table 3.3 reports numerical results from estimating versions of equation (3.2), with standard errors clustered by pixel[18]. The negative coefficient associated to low-income households (i.e. Eligible) suggests that households with fewer resources are less likely to report losses of cultivable land, harvest, and animals. Possible explanations are that poor households might be more prone to plant despite adverse soil conditions, might be more likely to harvest whatever they can for subsistence, and tend not to have assets such as animals.

Table 3.4 allows us to compare self-reported losses for *eligible* and *non-eligible* households under different weather conditions: no shocks, drought and extreme rainfall. Coefficients in the fours lines are obtained by combining linearly estimated coefficients in table 3.3, columns (2), (5), (8) and (11) respectively. The baseline in each of the two groups (i.e. eligible and non-eligible) corresponds to households that did not experience any shock. The coefficient 0.105 in the first line, column (B), indicates that among non eligible households, the probability to report harvest losses is 10.5 percentage points higher for households that experienced a drought during the planting season compared to the baseline (i.e. non-eligible households that did

[18]The coupled effect of dry spells and intense rains occurring during the same harvest season (not included in table 3.3) did not provide significant results and did not affect the other coefficients.

not experience any shock). The occurrence of a drought seems to be associated to higher probability of reporting harvest losses for both non-eligible and eligible households (respectively 10.5 and 15.6 percentage points higher). Coefficients in columns B and E are not significant with respect to soil damages and loss of hardware. Among households experiencing a drought, only richer households (i.e. non-eligible) are more likely to report a loss of animals (by about 2 percentage points).

The scenario is darker in case of extreme rainfall: all coefficients in columns (C) and (F) are positive; and the likelihood of reporting losses is significantly higher for harvest, soil and hardware. In particular, extreme rainfall seems to be associated to higher probability of reporting harvest losses for both non-eligible and eligible households (about 18 percentage points higher).

Contraction in Consumption. A decline in agricultural productivity and asset losses induced by climatic shocks is expected to create liquidity constraints and eventually a contraction in households' consumption.

Table 3.5 reports results from estimating equation (3.4). Estimates present changes in the logarithm of total, food and non-food consumption associated to dry spell and intense rains controlling also for low-income group (E) and treatment (T). As expected, even in the absence of shocks, low-income households are characterized by lower consumption levels, in the saturated model (columns (6) and (9)) the coefficients associated to low income households corresponds to -9% in food consumption and -54% in non-food consumption. The interaction between low-income and treated ($E_{hvp} * T_{vp}$) is a categorical variable equal to 1 for low-income households that actually received Progresa benefits.

Given the high number of interaction terms in table 3.5, in order to facilitate the interpretation of my estimates, I have linearly combined the coefficients in columns (6) and (9). Results are presented in table 3.6, and allow to compare differences in post-shock food and non-food consumption for eligible and non eligible households, in treated and non-treated villages. Each coefficient represents the difference in log consumption with respect to the baseline (column (A)), for instance: the coefficient in column (B), first row, refers to eligible households in non-treated villages and represents the difference in log food consumption between households affected by a drought and the baseline (households that did not experience any shock). The general picture emerging from table 3.6 is that droughts and extreme rainfall events are associated with contractions in both food and non-food consumption for both eligible and non-eligible households.

I have performed robustness checks using absolute precipitation in the spring and fall as independent variables, including a village fixed-effect and with standard errors clustered by pixel. Results show that: (i) spring precipitation has no effect on consumption; (ii) fall precipitation has positive effect on food consumption; and (iii) fall precipitation has negative effect on non-food consumption for poor-non-treated households. The positive impact on food consumption might suggest non-linearities in the effect of precipitation which is otherwise captured by the model including binary variables for shocks.

A closer look at the results in table 3.6 shows that there are differences in impacts across income groups. Let's focus first on food consumption. Food consumption of poor households (i.e. eligible) does not seem significantly affected by droughts, while for non-eligible households the estimated contraction in food consumption is about 5-9%. The coefficients associated to extreme rainfall events (columns (C) and (F)) are all negative; however, poor and treated households (i.e. eligible in treated villages) do not present a significant contraction in food consumption. In absence of treatment, poor households are associated to an 18% contraction, which is larger in both absolute and relative terms than the contraction experienced by non-eligible households. Among non-eligible households extreme rainfall is associated to a 8-12% contractions in food consumption compared to households that did not experience shocks.

Non-food consumption is strongly and significantly affected for all households with contractions of 21-36%. It is worth noting that contractions in food consumption are always smaller compared to non-food consumption. This is not surprising, households facing severe income shocks are more likely to smooth food consumption first while reducing non-food consumption.

Extreme rainfall events seem to have stronger negative impacts compared to dry spells, except for eligible and treated households. There are several possible explanations: (i) the first is timing, droughts in 1998 and 1999 started before the beginning of the agricultural season, thus households could plan ahead and diversify their income generating activities; (ii) the second is the duration of the shock, droughts usually persist multiple months, and rural households could make long-term decisions to adjust (e.g. seasonal migration of household members to other states); (iii) the third is experience, Mexico is historically prone to persistent droughts and households might have developed strategies to adjust during dry spells.

Conditional Cash Transfer Table 3.7 allows us to interpret the role of the randomized conditional cash transfer Progresa in absence of shocks. Coefficients in columns (3) represent the difference in log food and log non-food consumption between eligible and non-eligible households in treated and control villages. The only significant coefficient is the difference in food consumption for eligible households; Progresa seem to increase food consumption of eligible households by 9.47%, but it does not seem to affect their non-food consumption. This confirms that treatment achieved one of Progresa's goals by successfully increasing food consumption for low-income households. The government intervention does not seem to change consumption of non-eligible households, which suggests that there are no spillover effects or transfers between eligible and non-eligible households.

The interaction between the conditional cash transfer and weather shocks represents an additional level of analysis. Table 3.8 shows differences in post-shock food consumption between eligible and non-eligible households in treated and control villages, after droughts (in column (6)) and extreme rainfall (in column (9))[19]. Progresa seems to have benefited only eligible households affected by rainfall: the difference in food consumption between treated and non-treated households is about 15%. There are no significant differences associated to droughts. Non-eligible households facing weather shocks do not benefit from Progresa, which suggests that there are no intra-village transfers. Results for non-food consumption are similar (Table 3.8, columns (6) and (9)): the difference in non-food consumption between treated and non-treated households after extreme rainfall events is about 15%.

Low-income households appear to be more vulnerable to intense rains than higher income groups, the coefficient associated to the interaction of intense rain and poor ($R_{pt} * E_{hvp}$) is a significant -5% in food consumption. An important result is that this negative impact is perfectly compensated by eligible households receiving treatment. Progresa represents a sort of insurance mechanisms that allowed low income households to smooth consumption in case of unexpected punctual income shocks (extreme rainfall events).

Prolonged Effects of Exogenous Shocks. The next empirical exercise tests the hypothesis that the liquidity constraints induced by income shocks might have protracted consequences over the next agricultural season. Table 3.9 reports results from estimating equation (3.5) for total, food and non-food consumption. Even in the absence of shocks, low-income households are characterized by lower consumption

[19] coefficients are obtained by combining linearly estimates in table 3.5 (columns(6) and (9))

levels[20].

Linear combinations of estimates are presented in table 3.10. Non-food consumption levels of households hit by weather shocks are still significantly contracted, for both eligible and non-eligible households, even in treated villages.

Results for food consumption are less homogeneous. Let's focus first on food consumption of *eligible households* (first row). We observe three interesting results. First, non-treated households present persistent negative effects one year after extreme rainfall shocks (column (C)). Second, treated households that did not face weather shocks in 1998 (column (D)) are associated to a 17% higher food consumption compared to the baseline (i.e. non-treated households that did not experience weather shocks in 1998). Third, food consumption of households that did face a drought in 1998 is 7% higher compared to the baseline (i.e. non-treated households that did not experience weather shocks in 1998). From these results emerges that extreme rainfall events, unlike droughts, have a protracted negative impact on food consumption of eligible households, and that Progresa was successful in improving food consumption in eligible households even if affected by weather shocks in 1998.

Let's now look at food consumption of *non-eligible households*. In non-treated villages, households affected by a drought in 1998 were able to smooth consumption while households hit by extreme rainfall events in 1998 present a persistent contraction of about 13% compared to households that did not experience shocks. This suggests that extreme rainfall events in 1998 generated persistent impacts. In treated villages, there are two very interesting results: first, extreme rainfall events did not generate persistent impacts; and second, food consumption of households that did not face shocks in 1998 is actually 12% higher compared to non-treated households. These

[20] The coefficient associated to *Eligible* corresponds to -8% for food consumption and -49% for non-food consumption

results seem to suggest the occurrence of Progresa spillover effects (inter-household transfers) associated to food consumption to non-eligible households.

The beneficial effect of Progresa on food consumption of all households in treated villages is confirmed by coefficients in table 3.11. Column (3) presents the difference in food consumption between treated and non-treated villages (without considering possible interactions between treatment and weather shocks). The two coefficients in column (3) suggest that there is a significantly positive difference in food-consumption between households in treated and control villages; this difference in consumption associated to Progresa corresponds to +17% for eligible households and +12% for non-eligible households. There seem to be no differences in non-food consumption between households in treated and control villages. Progresa benefits seem to have been canalized toward food consumption.

Table 3.12 shows the effect of the interaction between treatment and weather shocks. Let's look first at households that experienced a drought in 1998: eligible households in treated villages have a 7% higher food consumption than comparable households in non-treated villages; for non-eligible households the difference in food consumption between treated and non-treated villages is not significant.

The interaction between Progresa and extreme rainfall events presents different outcomes. Both eligible and non-eligible households in treated villages affected by extreme rainfall in 1998 benefited from Progresa. The difference in food consumption between households in treated and non-treated villages is 21% for eligible households and 11.42% for non-eligible households. Sharing of Progresa benefits seem to have occurred after extreme rainfall shocks .

There are not significant differences in non-food consumption between treated and non-treated villages, with one exception: eligible households in treated villages consume about 13% more than comparable households in control villages.

From the results just described we can conclude that, one year after the beginning of the Progresa pilot, the program seem to have generated two positive outcomes:(i) it has improved food consumption of eligible treated households; and (ii) it has also indirectly benefited food consumption of non-eligible households in treated villages that in 1998 where not affected by weather shocks or that experienced extreme rainfall events. We do not observe positive spillovers in villages affected by droughts in 1998. These results will be further discussed in section 3.5.2.

Vulnerability and Resilience of Low-income Households. From the above discussion on the results in Tables 3.6 and 3.10 emerges that low income household are more vulnerable to income shocks. In particular, coefficients in table 3.6 (column (C)) show that immediately after intense rains occurred, eligible (i.e. poor) households experienced an -18% contraction (first row) in food consumption compared to the baseline (i.e. poor households that did not face any shocks), while non-eligible households experience a -13% contraction compared to the baseline (i.e. non-eligible households that did not face any shocks). The difference in food consumption associated to poor households is larger in both absolute and relative terms than the one experienced by non-eligible households.

Impacts of sudden extreme rainfall events may be more severe for poor households for a variety of possible reasons. First, poorly built housing units are more likely to be damaged by heavy precipitation. Second, poor households in mountainous regions usually have access to lower-value land (e.g. poor soils on steep slopes) and consequently their harvest is more likely to be compromised by intense surface runoff. Third, poor households in rural areas are more likely to rely almost exclusively on agriculture instead of diversifying their income-generating activities; a sudden weather shock during harvest season does not allow them to adapt and might translate into a major perhaps even insurmountable loss for the household.

In absence of treatment poor households appear to be also less resilient to extreme precipitation. Table 3.10 is analogous to 3.6 and provides insights about impacts on food and non food consumption one year after weather shocks occurred. Coefficients in this table provide us with a measure of resilience to shocks, small or insignificant coefficients indicating that households were able to overcome the shock and adjust their consumption to levels comparable to the baseline (i.e. households that did not experience any shock). Column (C) shows that one year after extreme rainfall events occurred, in non-treated villages, eligible (i.e. poor) households were still associated to a -17% difference (first row) in food consumption compared to the baseline (i.e. poor households that did not face any shocks), while non-eligible households experienced a -13% difference compared to the baseline (i.e. non-eligible households that did not face any shocks). The difference of food consumption associated to poor households is still larger in both absolute and relative terms than the one experienced by non-eligible households.

3.5.2 Mitigation by Progresa

Progresa was designed to reduce poverty by targeting nutrition, health, and educational attainment. Results in table 3.7 suggest that in the absence of climatic shocks, treated households reported higher food consumption (about 9% more) than non-treated families of comparable income. Such results are consistent with the literature on Progresa evaluations (Skoufias et al, 2001). Two more important results emerge from my analysis and will be further discussed below.

Partial Consumption Smoothing. In 1998 and 1999 the months of September and October were characterized by abnormally intense rainfall. According to the Progresa survey schedule, households consumption was measured at the end of October. My estimates for food consumption (table 3.5, column (6), coefficient $R \times E$) suggest that low-income household were more vulnerable to intense rains than higher income groups. However, the almost-immediate negative impact (-5%) of intense rains on food consumption of low-income households seem to have been completely smoothed by treatment for beneficiary households (table 3.6, columns (C) and (F)). Progresa cash transfers appear to have reduced the vulnerability of poor beneficiary households acting as a partial insurance mechanism by smoothing food consumption.

Informal Insurance at the village level. Progresa benefits started being distributed in May 1998. In villages randomly selected for treatment and untouched by the 1998 climatic shocks, by November 1999 Progresa had increased food-consumption for all households, including non-eligible households. The beneficial effect of treatment can be seen in table 3.11, column (3)[21], where the coefficients associated to food consumption in treated villages are positive and significant and correspond to an increase of 17% and 12% for eligible and non-eligible households respectively (compared to households in non-treated villages). In treated villages Progresa benefits combined with informal insurance mechanisms (such as inter-household food or monetary transfers) seem to have generated an increase in wealth with positive externalities on food consumption at the village level. Non-food consumption was not affected (Table 3.11, column (6)).

In treated villages affected by weather shocks in 1998, Progresa's benefits on food-consumption depend on the nature of the shock:

[21] As well as table 3.10, column (D)

- after droughts, only eligible households in treated villages present a food consumption level significantly higher 7% than comparable households in non-treated villages. There does not seem to be any spillover effect to non-eligible households (Table 3.12 column (6)).

- after extreme rainfall events, both eligible and non-eligible households in treated villages present a level of food consumption significantly higher (respectively, 22% and 11%) than comparable households in non-treated villages (Table 3.12 column (9)).

These results seem to suggest that after extreme rainfall events inter-household transfers effectively increased food consumption at the village level. One possible explanation is the unexpected nature of the shock, which might trigger solidarity at the village level. Droughts are progressive, persistent events and households might have time to adapt. Another element to take into account is timing: droughts occurred at the beginning of the agricultural season, during the planting phase, when households still had time to find alternative income generating activities. Floods, on the other hand, occurred at the end of the agricultural season leaving to when harvest losses were inevitable and there was no time to adjust. Another dimension differing between the two types of shock is their distribution: floods might affect households of the same village in a different way, while droughts are a covariate shock. Inter-household transfers as informal insurance mechanisms are less likely to occur when the whole village is affected by the shock. The perception of damages incurred are also different, impacts of floods might be more sudden but also more visually startling and prompt households to share with neighbors.

3.5.3 Migration

When inter-household transfers and other informal insurance strategies (e.g. crop diversification and asset depletion) are not sufficient to protect consumption, temporary or permanent migration of household members can be a possible solution. Migration of family members allows geographic diversification of incomes and might help protecting consumption at the household level. This section will explore the determinants of the decision to migrate.

Timing and Destination The Progresa 1998 and 1999 surveys contain detailed questions about emigration of household members, including month of departure and destination. Figure 3.3 (top) shows the distribution of migrants in the 1990s. The number of migrants increased dramatically in 1997 and then even more in 1998. Recent literature has found strong correlation between rainfall shocks (i.e. droughts) and Mexican migration (Yang and Pugatch (2010); Feng et al. (2010)). Figure 3.3 (middle and bottom) shows the month of departure of migrants who left to look for work in 1998 and 1999 and did not return. Bars of different colors indicate if the migrant departed from a region that: (i) did not experience any climatic shocks, (ii) experienced a drought in April May, (iii) experienced severe rainfall. The peak of migration in May corresponds with the end of the planting season. A possible explanation might be that seasonal workers who usually leave their communities in May, instead of coming home at the end of the season chose to work in a different location, due to economic hardship in their home villages. It is also worth noting that there is large percentage of migrants leaving in September and October 1998 from regions hit by extreme rainfalls. Figure 3.4 presents the destinations of migrants. Bars of different colors indicate the shocks experienced in their communities of origin. The majority of migrants from villages hit by droughts moved to a different state or abroad, in localities that were probably distant enough not to be affected by the climatic shock.

Effect of Progresa on Migration of a Family Member. I created a binary variable equal to 1 if the household reported that one member migrated and did not return in the previous 12 months (M_{hvp}). I considered only migrants who left to other Mexican states or moved abroad for professional and economic reasons. Unfortunately the available data could not provide information on migration of entire households. I expected climatic shocks to increase the probability to migrate. Migration to distant destinations requires itself an initial investment. Are poor and non-poor equally likely to migrate? Citing a theoretical contribution by Banerjee and Newman (1998), Murdoch (1999) observes that lack of informal insurance social network in urban areas may inhibit mobility from villages. More specifically, only relatively rich and relatively poor (who never had much group based insurance to start with) will migrate. Poor households that rely heavily (and predominantly) on their social network as source of informal insurance might be less likely to migrate. To explore if climatic shocks, income, and Progresa transfers affect migration decisions at the household level equation (3.6) is estimated:

$$
\begin{aligned}
M_{hvpt} = {} & \alpha + \beta_1 D_{pt} + \beta_2 R_{pt} + \beta_3 E_{hvp} + \beta_4 T_{vp} + \phi_4 (E_{hvp} * T_{vp}) \\
& + \gamma_1 (D_{pt} * E_{hvp}) + \gamma_2 (D_{pt} * T_{vp}) + \gamma_3 (D_{pt} * E_{hvp} * T_{vp}) \\
& + \theta_1 (R_{pt} * E_{hvp}) + \theta_2 (R_{pt} * T_{vp}) + \theta_3 (R_{pt} * E_{hvp} * T_{vp}) + \delta_t + \varepsilon_{hvpt}
\end{aligned}
\tag{3.6}
$$

The model reproduces the main equation (3.4). The event that an household member migrates is regressed on the occurrence of climatic shocks (D_{pt} and R_{pt}), income group (E_{hvp}), residence in a treated village (T_{vp}) and their interactions.

Table 3.13 reports the results for equation (3.6): all migrants (columns 1-3), females (columns 3-6) and males (columns (6-9). In table 3.13 (column (3)) show estimates for the model where men and women are aggregated. We find that the coefficient associated to treatment T is positive and corresponds to ~ 0.04. These results are consistent with a recent study by Angelucci (2010). Angelucci used the Progresa dataset to estimate the effect of the potential grant size on migration. Her estimates suggest that the program is associated with an increase in international migration, which is also a positive function of size of the transfer.

In order to facilitate the interpretation of estimates in table 3.13 linear combinations of coefficients in columns (6) and (9), considering separately men and women, are provided in table 3.14. The main findings are outlined below.

First, extreme rainfall shocks seem to be associated to higher likelihood of migration for women in both eligible and non-eligible households, in both treatment and non-treated villages (columns (C) and (F)). This difference in probability of migration is consistently about 2 percentage points higher than the baseline for each category (i.e households that did not experience shocks, column (A)). Treated households are prevented from migrating by Progresa itself, in order to keep receiving the transfer eligible households must reside in the treated village. However, this would not prevent household members from engaging in temporary or permanent migration in times of need.

Second, in absence of shocks, Progresa by itself seems to affect the decision to migrate of family members. More particularly, in treated villages women in non-eligible households seem more likely to leave, with a probability that is 2 percentage points higher compared to non treated villages (table 3.15 column (3)). Why are non-eligible women and not eligible women more likely to migrate? One hypothesis could be that

Progresa triggers some redistributive mechanism within the village, that in turn reduce financial constraints of non-eligible households, while eligible households are still too poor to leave. Because of Progresa, in treated villages richer households might reduce their transfers to poor households, this might in turn loosen financial constraints of non-poor households and favor migration of a household member, particularly in case of drought.

Women are significantly affected by rainfall shocks. What does gender tell us about migration decisions? Why is migration of women and not men affected by weather shocks (particularly extreme rainfall events) in our dataset? Women might be temporary migrants, who leave temporarily to provide as secondary earners in times of financial need. Also, rainfall shocks occurred at end of the agricultural season (beginning of the summer) and it is possible that women are more likely to find non-agricultural positions (e.g. maids, domestic help in urban areas). Another possibility is that men "predisposed" to leave might have already left earlier in the 1990s in response to dry conditions. A broader investigation considering a longer time frame, differencing between men and women, and studying permanent versus temporary migration patterns might shed light on these results and on deepen our understanding of the motives and determinants of migration.

3.6 Conclusion

At the end of the 1990s, intense climatic shocks in parts of central Mexico imposed substantial liquidity constraints to rural households. As expected, in communities hit by major non-idiosyncratic income shocks, informal insurance mechanisms and inter-household transfers appeared to be ineffective. My estimates show that in these villages, low-income households were more vulnerable and less resilient to unexpected exogenous shocks (extreme rainfall) than higher-income households. Possible explanations are low assets and inability to diversify income-generating activities.

This paper exploits the randomized poverty-reduction program Progresa to measure the benefits of the public cash transfer in mitigating vulnerability to weather shocks. Poor households receiving Progresa benefits were able to at least partially smooth their food-consumption after extreme rainfall (unexpected/acute shocks).

I found two positive spillover effects of Progresa. First, immediately after weather shocks, Progresa had a mitigating effect; households receiving the cash transfer were less vulnerable to extreme rainfall events (unexpected/acute shocks) and able to partially smooth post-shock consumption. Second, in treated villages, one year after the beginning of the intervention (in 1999), Progresa benefits had spread to non-eligible households except for villages that experienced a drought in 1998. This seem to indicate that inter-household transfers and partial risk sharing at the village level are less likely in correspondence to persistent shocks (drought), and more likeley when acute shock (extreme rainfall events) or no shocks occur.

Another contribution of this paper is that it looks at the linkages between weather shocks and the decision to migrate of family members for different income groups, considering also the role played by the randomized cash transfer. My estimates show that after extreme rainfall shocks women's mobility increased. Also, the cash transfer seems to have increased mobility from treated villages in general, and especially women from richer households after droughts. These results require further investigation and might have important policy implications given the current climate projections; unmanaged and unexpected climate-related domestic or international migration can represent a major socio-political concern.

These findings about Mexico are significant from a global perspective given that subtropical regions are projected to experience increasing weather extremes and decreasing agricultural yields with climate change. This study also highlights that addressing risk can be an important complement to poverty-reduction programs. Further research on the design of vulnerability-reduction measures would benefit regions in Africa or Latin America that are strongly influenced by cyclical extreme climatic patterns (i.e. recurrent ENSO-related droughts and severe rainfall).

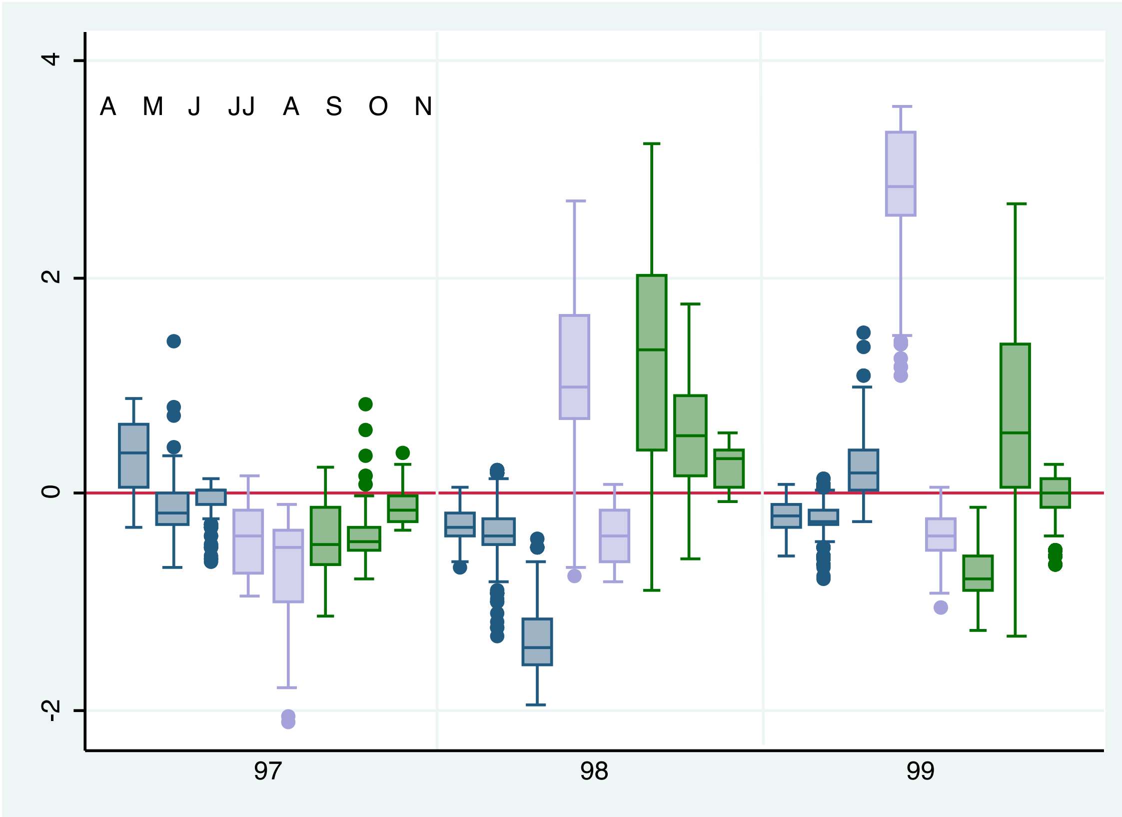


Figure 3.1: Monthly precipitation standardized anomalies (UEA-CRU-TS2p1, University of East Anglia Climate Research Unit) associated to the 506 Progresa villages during the agricultural season (April to November) of the years 1997-1999. The values on the vertical axis indicate the number of standard deviations from the climatology (i.e. the average precipitation in a given month in a given location over about 40 years (1960 - 1999)). April, May and June (A, M, J), correspond to the planting phase; July and August (JJ, A) correspond to the maturation phase; September, October and November (S, O, N) correspond to the harvest phase.

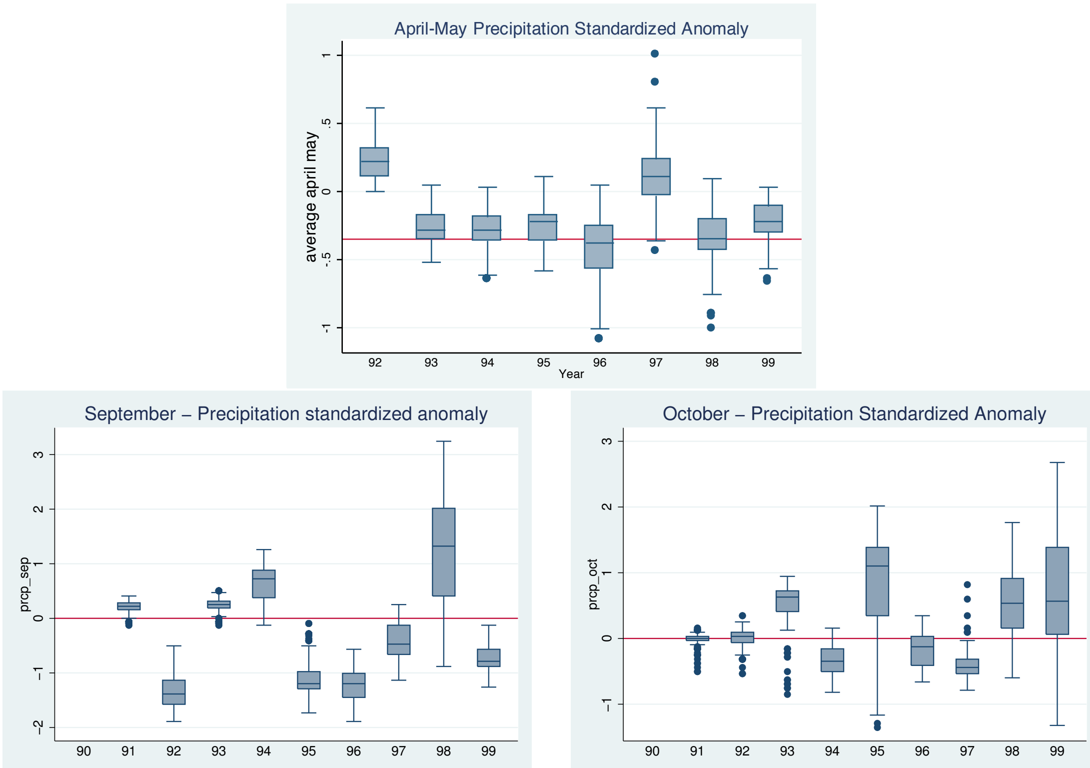


Figure 3.2: Precipitation standardized anomalies (UEA-CRU-TS2p1, University of East Anglia Climate Research Unit) associated to the 506 Progresa villages, for April-May (top), September (bottom-left) and October (bottom-right), from 1990 to 1999. The values on the vertical axis indicate the number of standard deviations from the climatology (i.e. the average precipitation in a given month in a given location over about 40 years (1960 - 1999)).

Table 3.1: Summary Statistics

	Mean	St. Dev.	Min	Max
self reported losses:				
i. harvest	.3097054	.4623772	0	1
ii. land (soil damages)	.0412023	.1987602	0	1
iii. animals	.0252379	.1568485	0	1
iv. hardware	.0039766	.0629354	0	1
drought (D)	.2546993	.4356967	0	1
extreme rain (R)	.5656819	.4956725	0	1
low-income households (E)	.5374076	.4986043	0	1
households in treated villages (T)	.6089086	.488	0	1
logarithm of:				
i. total consumption (per capita)	5.457258	.4989914	4.216136	6.921283
ii. food consumpt. (per Adults Equivalents)	5.234673	.5001911	1.496156	6.893197
iii. non-food consumpt. (per capita)	3.54429	.9543056	-2.302585	6.777045

$D = 1$ if the precipitation anomaly in April-May is $< -0.35(median)$
$R = 1$ if the precipitation anomaly in Sept-Oct is > 1

Table 3.2: Prevalence of weather shocks in control vs treatment villages. Villages were randomly selected to receive treatment (i.e. the conditional cash transfer Progresa). The occurrence of weather shocks (*drought* (D) during the planting phase and *extreme rain* (R) during the harvest phase is indicated by a binary variable calculated using the precipitation dataset UEA-CRU-TS2p1 (University of East Anglia Climate Research Unit).

	Control	Treatment	p-value
D drought in 1998	45.7	42.2	0.4433
D drought in 1999	9.7	9.5	0.94
R extreme rain in 1998	60.2	60.6	0.9277
R extreme rain in 1999	51.3	47.3	0.3828

$D = 1$ if the precipitation anomaly in April-May is < -0.35 (median)
$R = 1$ if the precipitation anomaly in Sept-Oct is > 1

Table 3.3: Effect of weather shocks on self reported losses. The occurrence of weather shocks (Either *drought* during the planting phase or abnormally *extreme rain* during the harvest phase) is indicated by binary variables calculated using the precipitation dataset UEA-CRU-TS2p1 (University of East Anglia Climate Research Unit).

	Loss of Harvest			Soil Damage			Loss of Animals			Loss of Hardware		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
D	0.131**	0.105**	0.114**	0.0120	0.0157	0.0173	0.0129	0.0188**	0.0240**	-0.000726	-0.000664	0.000641
(drought)	[0.0527]	[0.0470]	[0.0500]	[0.00931]	[0.0110]	[0.0130]	[0.00854]	[0.00880]	[0.0112]	[0.000871]	[0.00109]	[0.00154]
R	0.170***	0.177***	0.216***	0.0254***	0.0252***	0.0299***	0.00750	0.0110	0.0131*	0.00475**	0.00437*	0.00515***
(extreme rainfall)	[0.0428]	[0.0444]	[0.0503]	[0.00750]	[0.00828]	[0.0111]	[0.00689]	[0.00697]	[0.00772]	[0.00226]	[0.00259]	[0.00183]
E		-0.0608***	-0.0883***		-0.00709**	-0.0132**		0.000944	-0.00232		-0.000764	0.000207
(eligible household)		[0.0160]	[0.0216]		[0.00344]	[0.00508]		[0.00261]	[0.00321]		[0.00109]	[0.000687]
$D \times E$		0.0504**	0.0598*		-0.00672	-0.00733		-0.0106**	-0.00655		-0.0000482	0.000424
		[0.0233]	[0.0314]		[0.00693]	[0.0105]		[0.00418]	[0.00557]		[0.00144]	[0.00161]
$R \times E$		0.00311	0.0409		0.00371	0.00960		-0.00624*	-0.00384		0.00000257	-0.00194
		[0.0198]	[0.0277]		[0.00470]	[0.00859]		[0.00337]	[0.00511]		[0.00184]	[0.00180]
T			0.0291			-0.00533			0.00598			0.00263*
(treated village)			[0.0299]			[0.00490]			[0.00401]			[0.00142]
$E \times T$			0.0440			0.0103*			0.00518			-0.00166
(treated household)			[0.0311]			[0.00528]			[0.00380]			[0.00132]
$D \times T$			-0.0165			-0.00342			-0.00871			-0.00211
			[0.0397]			[0.0125]			[0.0108]			[0.00238]
$D \times E \times T$			-0.0183			0.000859			-0.00635			-0.000632
			[0.0354]			[0.0111]			[0.00654]			[0.00221]
$R \times T$			-0.0657			-0.00796			-0.00347			-0.00130
			[0.0437]			[0.00948]			[0.00776]			[0.00351]
$R \times E \times T$			-0.0589*			-0.00934			-0.00400			0.00315
			[0.0344]			[0.0101]			[0.00610]			[0.00303]
mean	0.31	0.31	0.31	0.041	0.041	0.041	0.025	0.025	0.025	0.0039	0.0039	0.0039
N	44975	43248	43248	44779	43061	43061	44774	43056	43056	44762	43043	43043
adj. R^2	0.050	0.053	0.056	0.009	0.009	0.010	0.006	0.007	0.007	0.003	0.003	0.003

$D = 1$ if the precipitation standardized anomaly in April-May is < -0.35; $R = 1$ if the precipitation standardized anomaly in Sept-Oct is > 1
Year fixed effect. Standard errors clustered by gridcell [in brackets]
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: Relationship between weather shocks and self-reported agricultural losses. Coefficients in each row are obtained by linearly combining coefficients in table 3.3, in columns 2, 5, 8 and 11 respectively.

	Non-Eligible			Eligible		
	No Shock (A)	Drought (B)	Extreme Rain (C)	No Shock (D)	Drought (E)	Extreme Rain (F)
Loss of Harvest	-	0.105	0.177	-	0.1558	0.1802
(mean=0.31)	[-]	[0.028]	[0.000]	[-]	[0.010]	[0.000]
Soil Damages	-	0.0157	0.0252	-	0.009	0.0289
(mean=0.042)	[-]	[0.158]	[0.003]	[-]	[0.317]	[0.000]
Loss of Animals	-	0.0188	0.011	-	0.008	0.0048
(mean=0.025)	[-]	[0.036]	[0.118]	[-]	[0.339]	[0.493]
Loss of Hardware	-	-0.001	0.004	-	-0.001	0.004
(mean=0.004)	[-]	[0.545]	[0.097]	[-]	[0.511]	[0.034]

[P-Values in brakets]

Table 3.5: Impact of weather shocks on log of consumption, and mitigation by Progresa (Equation 3.4)

	Total			Food			Non-Food		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
D (dry spell)	-0.124***	-0.139***	-0.108***	-0.0875***	-0.102***	-0.0599*	-0.302***	-0.270***	-0.262***
	[0.0281]	[0.0283]	[0.0335]	[0.0280]	[0.0265]	[0.0323]	[0.0701]	[0.0663]	[0.0696]
R (extreme rain)	-0.184***	-0.163***	-0.168***	-0.144***	-0.124***	-0.128***	-0.370***	-0.305***	-0.296***
	[0.0299]	[0.0316]	[0.0413]	[0.0275]	[0.0289]	[0.0363]	[0.0632]	[0.0602]	[0.0799]
E (eligible household)		-0.149***	-0.197***		-0.0599***	-0.0999***		-0.488***	-0.548***
		[0.0166]	[0.0222]		[0.0138]	[0.0186]		[0.0424]	[0.0613]
$D \times E$		0.0304**	0.0431*		0.0268*	0.0266		-0.0457	0.00927
		[0.0152]	[0.0237]		[0.0140]	[0.0217]		[0.0419]	[0.0566]
$R \times E$		-0.00415	-0.0337		-0.0187	-0.0500**		-0.00949	-0.0670
		[0.0209]	[0.0283]		[0.0177]	[0.0238]		[0.0564]	[0.0725]
T (treated village)			0.0174			0.0336			-0.0175
			[0.0230]			[0.0202]			[0.0493]
$E \times T$ (households that received treatment)			0.0741***			0.0611***			0.0943
			[0.0220]			[0.0197]			[0.0669]
$D \times T$			-0.0503			-0.0682**			-0.0125
			[0.0309]			[0.0304]			[0.0578]
$D \times E \times T$			-0.0138			0.00778			-0.0826
			[0.0276]			[0.0263]			[0.0637]
$R \times T$			0.00961			0.00701			-0.0141
			[0.0378]			[0.0359]			[0.0697]
$R \times E \times T$			0.0478			0.0509*			0.0923
			[0.0301]			[0.0268]			[0.0755]
mean	5.45	5.45	5.45	5.23	5.23	5.23	3.53	3.53	3.53
N	46337	44523	44523	46317	44505	44505	45714	43919	43919
adj. R^2	0.045	0.066	0.073	0.043	0.048	0.056	0.057	0.125	0.127

$D = 1$ if the precipitation standardized anomaly in April-May is < -0.35; $R = 1$ if the precipitation standardized anomaly in Sept-Oct is > 1
Year fixed effect. Standard errors clustered by gridcell [in brackets]
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Linear combination of coefficients in table 3.5, columns (6) and (9).

	Eligible Households (Poor)					
	Non-Treated			Treated		
	No Shock (A)	Drought (B)	Extreme Rain (C)	No Shock (D)	Drought (E)	Extreme Rain (F)
Food (mean=181.27*)	- [-]	-0.033 [0.340]	-0.178 [0.000]	0.09 [0.000]	0.001 [0.974]	-0.025 [0.450]
Non-Food (mean=27.11**)	- [-]	-0.253 [0.001]	-0.363 [0.000]	0.076 [0.329]	-0.272 [0.004]	-0.2078 [0.022]
	Non-Eligible Households					
Food (mean=200.34*)	- [-]	-0.059 [0.068]	-0.128 [0.001]	0.0336 [0.101]	-0.0945 [0.003]	-0.0873 [0.004]
Non-Food (mean=44.70**)	- [-]	-0.262 [0.000]	-0.292 [0.000]	-0.0175 [0.724]	-0.2923 [0.001]	-0.3274 [0.000]

[P-Values in brakets]; * Pesos per Adult Equivalents; ** Pesos per Capita

Table 3.7: Linear combination of coefficients in table 3.5, columns (6) and (9). Impact of randomized conditional cash transfer Progresa: difference in log food and log non-food consumption between eligible and non-eligible households in treated and control villages. In this table weather shocks are not taken into account.

	LOG FOOD CONSUMPTION			LOG NON-FOOD CONSUMPTION		
	Non Treated Village (1)	Treated Village (2)	Difference [2 − 1] (3)	Non Treated Village (4)	Treated Village (5)	Difference [5 − 4] (6)
Non Eligible (I)	- [-]	0.0336 [0.101]	0.0336 [0.101]	- [-]	-0.0175 [0.724]	-0.0175 [0.724]
Eligible Households (II)	-0.10 [0.000]	-0.0052 [0.819]	0.0947 [0.000]	-0.548 [0.000]	-0.471 [0.000]	0.0768 [0.329]
Difference ($I - II$)	0.10 [0.000]	0.0388 [0.009]		0.548 [0.000]	0.454 [0.000]	

[P-Values in brakets]
Average Food Consumption: Eligible = 181.27 Pesos per Capita; Non-Eligible = 200.34 Pesos per Capita
Average Non-Food Consumption: Eligible = 27.11 Pesos per Capita; Non-Eligible = 44.70 Pesos per Capita

Table 3.8: Linear combination of coefficients in table 3.5, columns (6) and (9). Difference in log food and log non-food consumption between eligible and non-eligible households in treated and control villages after droughts and extreme rainfall.

	LOG FOOD CONSUMPTION					
	Drought			Extreme Rainfall		
	Non Treated Village (1)	Treated Village (2)	Difference [5 − 4] (3)	Non Treated Village (4)	Treated Village (5)	Difference [8 − 7] (6)
Non Eligible (I)	-0.059 [0.068]	-0.0945 [0.003]	-0.0346 [0.193]	-0.128 [0.001]	-0.0873 [0.004]	0.0406 [0.202]
Eligible Households (II)	-0.1332 [0.001]	-0.0989 [0.004]	0.0343 [0.232]	-0.2779 [0.000]	-0.1252 [0.000]	0.1527 [0.000]
Difference ($I - II$)	0.0733 [0.000]	0.0044 [0.794]		0.1499 [0.000]	0.0378 [0.067]	
	LOG NON-FOOD CONSUMPTION					
Non Eligible (I)	-0.262 [0.000]	-0.2923 [0.001]	-0.03 [0.665]	-0.292 [0.000]	-0.3274 [0.000]	-0.0316 [0.597]
Eligible Households (II)	-0.8007 [0.000]	-0.8191 [0.000]	-0.0184 [0.806]	-0.9104 [0.000]	-0.7555 [0.000]	0.155 [0.006]
Difference ($I - II$)	0.5384 [0.000]	0.5268 [0.000]		0.6147 [0.000]	0.4281 [0.000]	

[P-Values in brakets]

Average Log Food Consumption = 5.2 Pesos per capita; Average Log Non-Food Consumption = 3.54 Pesos per capita

Table 3.9: Estimates of model 3.5 with log consumption as dependent variable. This is a cross-section for 1999, and variables D_{t-1} and R_{t-1} indicate shocks occurred in 1998.

	Total			Food			Non-Food		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
D_{t-1}	-0.108***	-0.114***	-0.0631	-0.0688**	-0.0728**	-0.00357	-0.239***	-0.246***	-0.268***
	[0.0303]	[0.0327]	[0.0418]	[0.0325]	[0.0330]	[0.0385]	[0.0452]	[0.0479]	[0.0608]
R_{t-1}	-0.211***	-0.186***	-0.192***	-0.154***	-0.135***	-0.133***	-0.442***	-0.357***	-0.365***
	[0.0286]	[0.0325]	[0.0414]	[0.0302]	[0.0328]	[0.0380]	[0.0463]	[0.0492]	[0.0615]
E (eligible household)		-0.158***	-0.210***		-0.0722***	-0.108***		-0.424***	-0.487***
		[0.0197]	[0.0301]		[0.0173]	[0.0274]		[0.0449]	[0.0545]
$D_{t-1} \times E$		0.00169	0.00281		-0.00313	-0.00574		0.00352	-0.0155
		[0.0233]	[0.0335]		[0.0219]	[0.0340]		[0.0576]	[0.0617]
$R_{t-1} \times E$		-0.00113	-0.0221		-0.00797	-0.0405		-0.0448	-0.0820
		[0.0248]	[0.0334]		[0.0215]	[0.0314]		[0.0571]	[0.0621]
T (treated village)			0.0763***			0.120***			-0.0478
			[0.0274]			[0.0257]			[0.0420]
$E \times T$ (treated household)			0.0779**			0.0498			0.0942
			[0.0329]			[0.0311]			[0.0572]
$D_{t-1} \times T$			-0.0845**			-0.114***			0.0362
			[0.0363]			[0.0348]			[0.0645]
$D_{t-1} \times E \times T$			0.0119			0.0188			0.0444
			[0.0385]			[0.0381]			[0.0662]
$R_{t-1} \times T$			0.00842			-0.00620			0.0147
			[0.0352]			[0.0333]			[0.0629]
$R_{t-1} \times E \times T$			0.0329			0.0519			0.0640
			[0.0351]			[0.0346]			[0.0626]
mean	5.40	5.40	5.40	5.16	5.16	5.16	3.65	3.65	3.65
N	22940	21126	21126	22934	21122	21122	22779	20984	20984
adj. R^2	0.051	0.078	0.093	0.027	0.033	0.053	0.069	0.135	0.138

$D_{t-1} = 1$ if the precipitation standardized anomaly in April-May 1998 is < -0.35
$R_{t-1} = 1$ if the precipitation standardized anomaly in Sept-Oct 1998 is > 1
Year fixed effect. Standard errors clustered by gridcell [in brackets]
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: Linear combination of coefficients in table 3.9, columns (6) and (9).

	Eligible Households (Poor)					
	Non-Treated			Treated		
	No Shock (A)	Drought (B)	Extreme Rain (C)	No Shock (D)	Drought (E)	Extreme Rain (F)
Food (mean=164.02)	- [-]	-0.0093 [0.844]	-0.173 [0.000]	0.17 [0.000]	0.066 [0.093]	0.043 [0.304]
Non-Food (mean=29.96)	- [-]	-0.284 [0.000]	-0.4468 [0.000]	0.0465 [0.503]	-0.157 [0.034]	-0.322 [0.000]
	Non-Eligible Households					
Food (mean=181.27)	- [-]	-0.0035 [0.926]	-0.1327 [0.001]	0.12 [0.000]	0.029 [0.941]	-0.0185 [0.566]
Non-Food (mean=49.40)	- [-]	-0.2684 [0.000]	-0.345 [0.000]	-0.048 [0.257]	-0.28 [0.000]	-0.398 [0.000]

[P-Values in brakets]

Table 3.11: Linear combination of coefficients in table 3.9, columns (6) and (9). Impact of randomized conditional cash transfer Progresa: difference in log food and log non-food consumption between eligible and non-eligible households in treated and control villages in 1999 (one year after beginning of cash transfer program). In this table weather shocks are not taken into account.

	LOG FOOD CONSUMPTION			LOG NON-FOOD CONSUMPTION		
	Non Treated Village (1)	Treated Village (2)	Difference [2 − 1] (3)	Non Treated Village (4)	Treated Village (5)	Difference [5 − 4] (6)
Non Eligible (I)	- [-]	0.12 [0.000]	0.12 [0.000]	- [-]	-0.048 [0.257]	-0.048 [0.257]
Eligible Households (II)	-0.108 [0.000]	0.0618 [0.016]	0.170 [0.000]	-0.487 [0.000]	-0.4405 [0.000]	0.0464 [0.503]
Difference ($I - II$)	0.108 [0.000]	0.0586 [0.003]		0.048 [0.257]	0.3927 [0.000]	

[P-Values in brakets]

Average Food Consumption: Eligible = 164.02 Pesos per Adult Equivalents, Non-Eligible = 182.27 Pesos per Adult Equivalents

Table 3.12: Linear combination of coefficients in table 3.9, columns (6) and (9). This table shows the effect of the interaction between Progresa Treatment and weather shocks. Column (3) and (6) present the difference in log food and log non-food consumption between households in treated and control villages in 1999, one year after droughts and extreme rainfall.

	LOG FOOD CONSUMPTION					
	Drought			Extreme Rainfall		
	Non Treated Village (1)	Treated Village (2)	Difference [5 − 4] (3)	Non Treated Village (4)	Treated Village (5)	Difference [8 − 7] (6)
Non Eligible (I)	-0.0035	0.0029	0.006	-0.1327	-0.0185	0.1142
	[0.926]	[0.941]	[0.825]	[0.001]	[0.566]	[0.001]
Eligible Households (II)	-0.117	-0.0427	0.0751	-0.282	-0.066	0.216
	[0.018]	[0.260]	[0.021]	[0.000]	[0.04]	[0.000]
Difference ($I - II$)	0.1141	0.0456		0.149	0.0473	
	[0.000]	[0.063]		[0.000]	[0.020]	
	LOG NON-FOOD CONSUMPTION					
Non Eligible (I)	-0.2684	-0.28	-0.0116	-0.345	-0.398	-0.033
	[0.000]	[0.000]	[0.874]	[0.000]	[0.000]	[0.559]
Eligible Households (II)	-0.771	-0.6439	0.127	-0.934	-0.8087	0.1252
	[0.000]	[0.000]	[0.122]	[0.000]	[0.000]	[0.041]
Difference ($I - II$)	0.50	0.364		0.569	0.41	
	[0.000]	[0.000]		[0.000]	[0.000]	

[P-Values in brakets]; Average Monthly Log Food Consumption = 5.15 Pesos/AE (AE indicates Adult Equivalents).

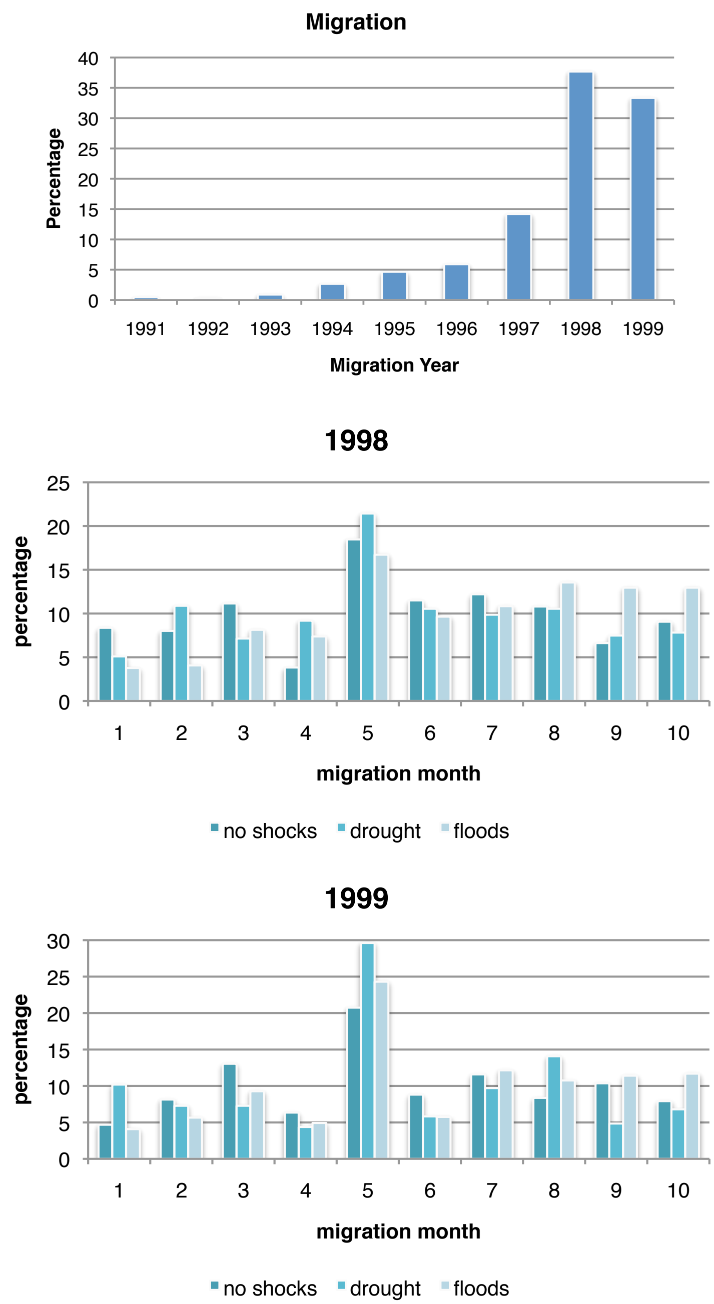


Figure 3.3: Top: reported migration of members of the households over 8 years (1992-1999). The second and third figure from he top show the percentage of migrants by month of departure in 1998 (middle) and 1999 (bottom). In these two figures bars of different colors indicate if the migrant departed from a region that: (i) did not experience any climatic shocks, (ii) experienced a drought, (iii) experienced only severe rainfall. The peaks of migration in May (5) correspond with the end of the planting season.

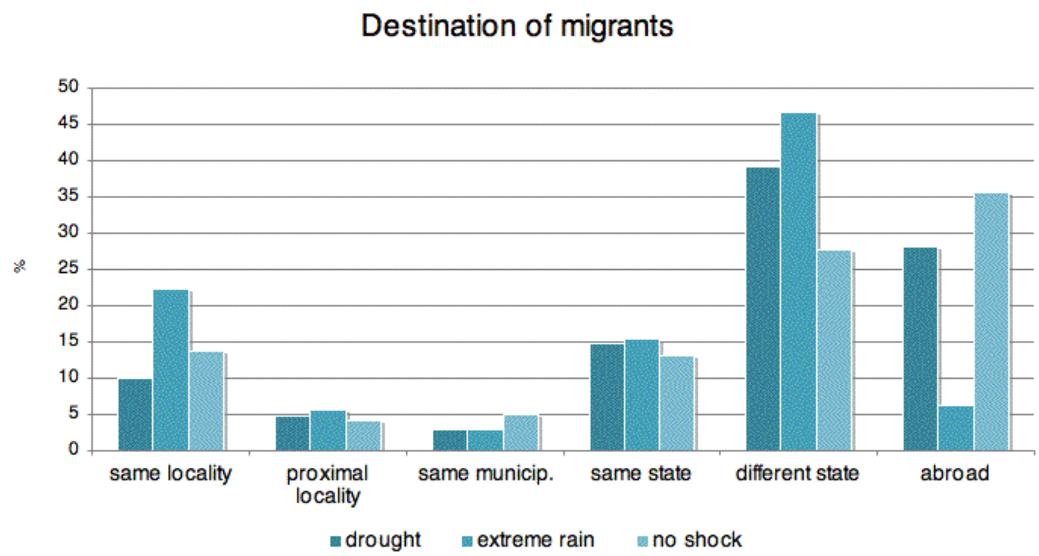


Figure 3.4: Destinations of migrants who left for professional reasons or economic problems in 1998-1999. Bars of different color indicate if the villages of origin were affected by climatic shocks or not. Almost 50% of migrants who left villages hit by extreme rain moved to a different state within Mexico. Legend for the x axis: 1 same locality; 2 a proximal locality; 3 a different locality of the same municipality ; 4 a locality in the same state; 5 a locality in a different state; 6 a foreign country.

Table 3.13: Climatic influence on the decision to migrate. The dependent variable is a binary variable equal to 1 if the household reports the departure of a member to a different state or abroad, for professional or financial reasons.

	All			Females			Males		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
D (drought)	0.0174**	0.0202*	0.0291*	0.00932**	0.0113**	0.0119	0.00813	0.00882	0.0172
	[0.00822]	[0.0115]	[0.0171]	[0.00365]	[0.00534]	[0.00732]	[0.00515]	[0.00725]	[0.0108]
R (extreme rainfall)	0.0197*	0.0109	0.0329*	0.0149***	0.00715	0.0207***	0.00478	0.00379	0.0123
	[0.0106]	[0.0136]	[0.0169]	[0.00514]	[0.00671]	[0.00760]	[0.00602]	[0.00782]	[0.0116]
E (eligible household)		-0.0182	0.000532		-0.00334	0.00360		-0.0149**	-0.00307
		[0.0132]	[0.0208]		[0.00790]	[0.0122]		[0.00691]	[0.0125]
$D \times E$		-0.00896	-0.0267		-0.00556	-0.00846		-0.00341	-0.0183
		[0.0112]	[0.0203]		[0.00647]	[0.0114]		[0.00685]	[0.0110]
$R \times E$		0.0165	-0.00544		0.0120	0.000450		0.00448	-0.00589
		[0.0121]	[0.0198]		[0.00726]	[0.0116]		[0.00717]	[0.0130]
T (treated village)			0.0364**			0.0193***			0.0171
			[0.0142]			[0.00500]			[0.0116]
$E \times T$ (treated household)			-0.0316			-0.0117			-0.0198
			[0.0198]			[0.0106]			[0.0138]
$D \times T$			-0.0143			-0.000577			-0.0138
			[0.0187]			[0.00864]			[0.0118]
$D \times E \times T$			0.0292			0.00446			0.0247*
			[0.0220]			[0.0120]			[0.0127]
$R \times T$			-0.0365**			-0.0224***			-0.0141
			[0.0166]			[0.00646]			[0.0129]
$R \times E \times T$			0.0371*			0.0194*			0.0177
			[0.0201]			[0.0110]			[0.0143]
mean	0.1	0.1	0.1	0.047	0.047	0.055	0.055	0.055	
N	33552	32401	32401	33552	32401	32401	33552	32401	32401
adj. R^2	0.095	0.099	0.100	0.049	0.051	0.052	0.041	0.044	0.044

$D = 1$ if the precipitation standardized anomaly in April-May is < -0.35; $R = 1$ if the precipitation standardized anomaly in Sept-Oct is > 1
E indicates households who are eligible to receive treatment (Progresa). T indicates villages that were randomly selected for treatment.
Year fixed effect. Standard errors clustered by gridcell [in brackets]; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.14: Linear combination of coefficients in table 3.13.

	Eligible Households (Poor)					
	Non-Treated			Treated		
	No Shock (A)	Drought (B)	Extreme Rain (C)	No Shock (D)	Drought (E)	Extreme Rain (F)
Women (mean=4.6%)	- [-]	0.0034 [0.709]	0.0211 [0.018]	0.0076 [0.386]	0.0149 [0.130]	0.0257 [0.009]
Men (mean=4.6%)	- [-]	0.0011 [0.860]	0.0064 [0.482]	-0.027 [0.796]	0.0071 [0.489]	0.0072 [0.493]
	Non-Eligible Households					
Women (mean=4.8%)	- [-]	0.0119 [0.108]	0.0207 [0.008]	0.0193 [0.000]	0.0307 [0.001]	0.0176 [0.018]
Men (mean=6.4%)	- [-]	0.0172 [0.118]	0.0123 [0.295]	0.017 [0.145]	0.0205 [0.128]	0.0153 [0.189]

[P-Values in brakets]

Table 3.15: Linear combination of coefficients in table 3.13. This table shows the impact of randomized conditional cash transfer Progresa on migration of a family member, between eligible and non-eligible households, in treated and control villages.

	Women (mean = 4.7%)			Men (mean= 5.5%)		
	Non Treated Village (1)	Treated Village (2)	Difference [2 − 1] (3)	Non Treated Village (4)	Treated Village (5)	Difference [5 − 4] (6)
Non Eligible (I)	- [-]	0.0193 [0.000]	0.0193 [0.000]	- [-]	0.0176 [0.145]	0.00176 [0.145]
Eligible Households (II)	0.0036 [0.768]	0.0112 [0.119]	0.008 [0.386]	0.003 [0.808]	-0.0057 [0.654]	-0.0027 [0.796]
Difference ($I - II$)	0.0036 [0.768]	0.008 [0.248]		0.003 [0.808]	0.0229 [0.002]	

[P-Values in brakets]

Table 3.16: Linear combination of coefficients in table 3.13. This table shows the effect of the interaction between Progresa Treatment and weather shocks. Column (6) and (9) present the difference migration of a family member between households in treated and control villages.

	Drought			Extreme Rainfall		
	Non Treated Village (1)	Treated Village (2)	Difference [2 − 1] (3)	Non Treated Village (4)	Treated Village (5)	Difference [5 − 4] (6)
Women (mean = 4.7%)						
Non Eligible (I)	0.0119	0.0307	0.0188	0.0207	0.0176	-0.0031
	[0.108]	[0.001]	[0.043]	[0.008]	[0.018]	[0.563]
Eligible Households (II)	0.0071	0.0185	0.0115	0.0247	0.0292	0.0045
	[0.536]	[0.031]	[0.274]	[0.008]	[0.000]	[0.453]
Difference ($I - II$)	0.0049	0.0121		-0.004	-0 .0117	
	[0.597]	[0.064]		[0.581]	[0.007]	
Men (mean= 5.5%)						
Non Eligible (I)	0.0172	0.0205	0.0035	0.0123	.0153	0.003
	[0.118]	[0.128]	[0.833]	[0.295]	[0.189]	[0.614]
Eligible Households (II)	-0.0042	0.0041	0.0082	0.0033	0.0042	0.0009
	[0.711]	[0.750]	[0.288]	[0.790]	[0.719]	[0.913]
Difference ($I - II$)	0.0213	0.016		0.009	0.0111	
	[0.138]	[0.043]		[0.236]	[0.026]	

[P-Values in brakets]

Chapter 4

Is ENSO an opportunity? Sharing risk across regions

Abstract[1]. This study explores the potential for re-insurance schemes built on regional climatic variability, and it represents the first exercise in trying to include El Niño Southern Oscillation (ENSO) in the design of rainfall insurance contracts. ENSO is an important component in modulating precipitation patterns in tropical Africa. The precipitation signals associated to cold and warm ENSO episodes in Southern and Eastern Africa are opposite and forecastable. This study focuses on micro-insurance contracts indexed on precipitation in 9 villages in Kenya, Tanzania (Eastern Africa) and Malawi (Southern Africa), and analyzes the contract payouts with respect to climate variability resulting from ENSO. In particular, (i) we simulated possible payouts using historical precipitation data and analyzed the differences between years with different ENSO states from 1961 to 2005; (ii) we applied Monte Carlo methods to simulate precipitation distributions in each location and calculated the mean and variance of payouts associated to different ENSO states. Our estimates indicate that more abundant rainfall reduces payouts and the risk of loan default during La Niña in southern Kenya and Malawi, and during El Niño in Tanzania. The

[1]This study was developed in collaboration with Alessandra Giannini (IRI, Columbia University) and Dan Osgood (IRI, Columbia University).

results of the Monte Carlo simulations go in the same direction.

4.1 Introduction

Climate change represents possibly the largest challenge in the history of the insurance industry but also a vast potential of business opportunities through the development of new financial instruments and practices. The chairman of Loyd's of London stated that climate change is the number-one issue for the insurance market; and Europe's largest insurer, Allianz, estimated that climate change will increase insured losses from extreme events in an average year by 37% within just a decade, with potential losses in a bad year of about $400 billions (Mills (2009)). UNEP has estimated the value of average yearly losses to be $1 trillion by the year 2040 (Dlugolecki (2006)). Insurance and reinsurance solvency might be at risk as a result of the projected higher frequency in natural catastrophes.

In the last decade insurers' perception of the risks posed by climate change has rapidly evolved, and the insurance industry has been actively pursuing climate change solutions to preserve private insurance markets and to expand to new markets in developing countries. Mills (2009) has documented an increasing number of actions implemented by insurers to improve disaster resilience and adaptation to climate change while mitigating climate risk; such actions include, for instance, programs promoting energy-efficiency, incentives for low-emission or loss-resilient profiles, and expansion of micro-insurance programs in developing countries.

The risk of insolvency and the issue of availability-affordability of insurance are also redefining the roles of the public sector and insurers in managing risk. Sustained increases in the frequency and/or intensity of extreme weather events will stress the government sector itself as a provider of insurance, and might also compromise the ability of governments to provide humanitarian assistance domestically and internationally in the event of disasters. Governments in developing countries, where insurance sector is weak or inexistent, are particularly vulnerable to weather-related risks and rely heavily on external aid in emergency situations.

Private-public partnerships are emerging as mutually beneficial strategies: government regulations may help insurers increase market penetration and geographic diversification, while reducing the likelihood that government will have to assume more climate risks if the private sector recedes. In order to transition from managing crisis to managing risks several governments are also engaging in the development of regional disaster risk pool and contingency funds. The Caribbean Catastrophe Risk Insurance Facility is the first regional disaster insurance facility and serves as a model for other regional institutions aimed at sharing risk across regions such as, for instance, the Pan African Disaster Risk Pool for Food Security[2] currently under development. National contingency funds and national weather indexed insurance contracts, such as those pioneered in Ethiopia and Malawi, can be expensive propositions for a single government. Larger schemes involving several governments, using a single instrument or a portfolio of instruments, and spreading risk across regions would be more financially efficient.

Insurers are also engaging in collaborations with climate scientists to design new products and improve existing instruments. A recent example is the partnership between the Earth Institute of Columbia University and Swiss Re to implement satellite-based remote sensing in support of micro-insurance for small farmers in Africa. Comprehensive satellite remote sensing datasets and Climate and Earth Science models

[2] The Pan African Disaster Risk Pool for Food Security is currently under development with the technical assistance of the UN World Food Programme, this institution would provide participating member states readily available cash in the event of a natural disaster.

are indispensable to complement information when ground data are insufficient to properly calibrate the pricing of weather-indexed insurance contracts (Brown et al. 2011) and when CAT models do not suffice. Climate science can also prove crucial in informing insurance on how to best integrate climate forecasts and spatial diversification in index insurance design to both reduce climate risks and promote development.

The need for regional coordination, private-public partnership and product design robustly rooted in scientific research are the three most important aspects emerging from the case study presented in this paper. The study focuses on micro-insurance contracts indexed on precipitation in 9 villages in Kenya, Tanzania (Southern Africa) and Malawi (Eastern Africa), we analyze the precipitation patterns associated with El Niño Southern Oscillation (ENSO) and we explore for the first time the potential for re-insurance schemes built on forecastable regional climatic patterns. We will argue that reinsurance schemes could be designed at the African continental scale taking advantage of climatic patterns in different regions. This study represents an exploratory framework that needs to be further refined and that can potentially be applied to other regions (e.g. Central and Latin America).

Africa represents a useful case study for its high vulnerability levels and low insurance availability:

"New studies confirm that Africa is one of the most vulnerable continents to climate variability and change because of multiple stresses and low adaptive capacity." Intergovernmental Panel for Climate Change (IPCC), 2007[3].

[3]Intergovernmental Panel for Climate Change (IPCC), Working Group II (WGII), Summary for Policy Makers (SPM), 2007

The inability to manage future climatic risks could represent a“poverty trap” for several African regions. Weather shocks can potentially destabilize not only households but entire countries. Government in drought-prone countries, donors and relief agencies are becoming aware of the importance to develop an ex-ante risk management framework for weather-risk. Joint efforts to develop innovative mechanisms to spread and pool risk (e.g. microinsurance and microcredit) are currently being designed in several African countries (Mills (2006), (2009)); however, insurance penetration is still at its lowest levels in the continent, particularly in rural areas.

According to the IPCC, climate change is likely to adversely affect both water availability and food security in the African continent; projections indicate that by 2020, between 75 and 250 million people are expected to be exposed to an increase of water stress. Agricultural production, including access to food, in many African regions is also projected to be severely compromised. In some countries, yields from rain-fed agriculture could be reduced by up to 50% by 2020, the area suitable for agriculture, the length of growing seasons and yield potential, particularly along the margins of semi-arid and arid areas, are also expected to decrease (IPCC, WGII, SPM, 2007). Besides climate change, climate variability associated with ENSO *teleconnections*[4] is another important factor to be considered in addressing issues of water management and food security in Africa. The ENSO signal translates into rainfall variability over Eastern Central and Southern Africa and it is strongly correlated

[4]Teleconnection patterns are crucial in determining climate variability over the African continent. The term ”teleconnection pattern” refers to a recurring and persistent, large-scale pattern of pressure and circulation anomalies that span vast geographical areas. Teleconnection patterns are also referred to as preferred modes of low-frequency (or long time scale) variability. Although these patterns typically last for several weeks to several months, they can sometimes be prominent for several consecutive years, thus reflecting an important part of both the interannual and interdecadal variability of the atmospheric circulation. Teleconnection patterns influence temperature, rainfall, storm tracks, and jet stream location/intensity over vast areas. Thus, they are often the culprit responsible for abnormal weather patterns occurring simultaneously over seemingly vast distances. (http://www.cpc.noaa.gov/data/teledoc/teleintro.shtml)

with extreme weather events. In an anthropogenically warming climate ENSO-related weather extremes might become more frequent and/or intense.

In an attempt to insure agricultural losses caused by weather extremes, the World Bank and other donors have been involved in working on crop insurance projects in the 1970s and 1980s. However, these efforts were soon abandoned as many of the problems with introducing multiple peril crop insurance became insurmountable constraints in developing countries (Hess and Syroka, 2005). The major limitations of traditional crop insurance relate to adverse selection and moral hazard issues. In order to overcome such implementation problems, rainfall indexed insurance has emerged as a preferred alternative. While conventional crop insurance is written against actual losses, index-based weather insurance is written against an objective physical trigger, such as cumulative rainfall during a certain period of time.

In this study we analyze index-based weather insurance contracts designed for Malawi, Kenya and Tanzania. A drought insurance scheme is currently under way in Malawi, while in Kenya and Tanzania similar weather-indexed insurance contracts are being developed but have not been tested yet. First implemented in 2005, the Malawi pilot scheme offers index-based weather insurance to smallholder groundnut farmers coupled with a loan for seeds and fertilizer; the aim of the experiment is to improve farmers' credit worthiness and therefore their ability to access credit for investing in higher-yield/higher return crops. Banks are not likely to be interested in lending to rainfed farmers with no collateral, in a drought prone region. By coupling bank loans with index-based weather insurance, farmers can receive the credit to purchase seeds and other agricultural inputs, and they can expect a net gain after repayment of the coupled loan-insurance contract (Osgood et al. 2007a).

While ENSO is an important component in modulating the rainfall regime in Southern Africa, the micro-insurance experiments currently under development to address weather risk among smallholder farmers in this region do not take into account forecastable ENSO climatic patterns yet. In the weather derivatives market climate, predictions are receiving more and more attention (Jewson and Brix 2005), however there is no available literature on the potential integration of seasonal forecasts in weather-indexed crop insurance schemes.

A few studies have explored the implications of ENSO-based forecasts in the context of common crop insurance contracts (Mjelde and Hill (1999), Cabrera et al (2006)). Cabrera et al. studied the interactions between conventional crop insurance and ENSO-based climate information for increasing farm income stability in a hypothetical Florida farm, and concluded that for high risk-averse farmers the best insurance strategy depends on the ENSO phase. A recent innovation in agricultural finance is the ENSO insurance in Peru. Indexed on monthly sea surface temperature[5], this product was presented to the Peruvian insurance regulators in 2010 as a form of business-interruption insurance designed to pay for consequential losses and extra costs linked to extreme flooding, which is highly correlated with ENSO (Skees and Collier (2010)). At this stage this product is not being offered to smallholder farmers, however an important and novel aspect of the ENSO insurance is that it pays before the catastrophe and it potentially represents also a mitigation strategy: educational efforts have focused on helping people in the target markets understand how to use the extra cash to mitigate the impending crisis.

This study describes a preliminary exercise in trying to include forecastable ENSO climatic patterns in the contract design of micro-insurance for maize in 9 villages in

[5]The ENSO insurance uses the monthly sea surface temperature for ENSO Region 1.2 (0-10 deg South, 80-90 deg West), measured and reported by the NOAA Climate Prediction Center.

Kenya, Tanzania (Eastern Africa) and Malawi (Southern Africa), and analyzes the contract payouts with respect to climate variability resulting from ENSO. In particular, (i) we simulated possible payouts using historical precipitation data and analyzed the differences between years with different ENSO states from 1961 to 2005; (ii) we applied Monte Carlo methods to simulate precipitation distributions in each location and calculated the mean and variance of payouts associated to different ENSO states. Our estimates indicate that more abundant rainfall reduces payouts and the risk of loan default during La Niña in southern Kenya and Malawi, and during El Niño in Tanzania. The results of the Monte Carlo simulations confirm the results for Kenya and Tanzania.

The remainder of the paper is structured as follows: section 2 offers a short description of the Malawi pilot scheme that combines micro-credit with weather index-based insurance; section 3 presents an overview of climatology, climate variability and seasonal climate forecasts in southern Africa and addresses the potential role of climate forecasts in reducing risk; section 4 describes the methodology we adopted in analyzing the contracts payouts with respect to climate variability. Section 5 concludes, discusses limitations, and presents challenges and perspectives.

4.2 Pilot Weather-Indexed Insurance Scheme in Malawi

In this section we provide background information for the Malawi pilot weather indexed insurance contracts, which are the only contracts actually implemented and represent the template for analogous contracts developed for Tanzania and Kenya but not implemented yet. The World Bank Commodity Risk Management Group (CRMG), in collaboration with local stakeholders, designed a weather insurance scheme in Malawi for the 2005/2006 crop season in order to enhance groundnut farmers' ability to manage drought risk and, in turn, access loans for improved agricultural inputs. Malawi was chosen for the insurance pilot project because it is one of the more drought-prone countries in the region. The country has experienced chronic food crises associated with droughts in 1991/92, 1994/95 and 1997/98. The general food security country context is as follows: the predominant staple food, maize, has very low yields; stock-piling at private and even public levels are underdeveloped; the financial system is weak and the government is preparing a new food security policy that seeks to determine the appropriate levels of strategic grain reserves (Hess, 2005).

Smallholder productivity characterizes Malawi's agricultural sector. Farmers often cultivate maize for subsistence purposes. Any surplus maize sold on the market fetches meager and unpredictable profits; therefore, smallholders tend to invest little in their crops. This under-investment is worsened by the limited access that smallholders often have to seed and fertilizer markets, particularly since fertilizer and chemicals are sold at a premium. As a result of all this, input suppliers have little incentive to cater to smallholders, especially in remote areas. Financial markets also fail rural producers because smallholders have very limited access to input financing. Rural financial services such as production credit for smallholders are virtually unavailable because of weather, government, moral risks, and high transaction costs in rural areas (Hess, 2005).

To address the credit constraints discussed above, bundled loan and insurance contracts were offered in four pilot areas: Kasungu, Nkhotakhota, Chitedze and Lilongwe. These pilot areas were chosen because the National Smallholder Farmers Association of Malawi (NASFAM), which was active supporting local farmers' associations to engage in growing groundnuts, had farmer clubs located near meteorological stations with reliable precipitation data. Additionally, the relatively good rain patterns for Malawi standards made the pilot scheme more feasible there (Osgood et al. 2007).

In November 2005, through their NASFAM clubs, 892 smallholder farmers bought the weather insurance that allowed them to access a loan package for 32 kilograms of improved groundnut seed (enough for cultivating one acre). The mechanism could be described as follows: before the rainy season, participating farmers receive improved agricultural inputs through a contract that specifies (i) an index-based weather insurance component, in which the premium is calculated based on the probability of a payout estimated using the entire available rainfall record (regardless of ENSO), and (ii) a loan component (at the end of the season the farmer will owe the lending institutions an amount equal to the cost of agricultural inputs plus insurance premium plus interest and taxes). If rains are good (as measured in a nearby weather station operated by the meteorological service), then the insurance company keeps the premium and farmers pay back the loan with proceeds from the (presumably good) harvest. If measured rains are below certain trigger values (based on critical stages of the groundnut growing season), then the insurance company pays part -or all- of the loan to the bank[6]. Since the farmers targeted by this scheme typically do not have legal title to their land, the insurance is used to guarantee the loan by requiring the

[6]For a more detailed description of the contract design, see UNDESA (2007).

farmer to purchase insurance so that the maximum liability is equal to the loan size including interest. The package is unitary, that is farmers cannot purchase partial packages or multiple packages (Osgood et al. 2007a).

Even though there is a significant relationship between the ENSO phenomenon and seasonal rainfall in Malawi, forecasts have not been integrated in the index-based weather insurance contracts' design for the first two years of piloting in Malawi. Premiums, payouts and other insurance parameters are set independently of the interannual variability in probability of drought occurrence. Similarly, the kinds and amounts of agricultural inputs to be loaned to farmers through credit do not reflect expected seasonal rainfall, even though they are given to farmers at a time when the seasonal forecast is already available (Osgood et al. 2007a). More details about the contract design are provided by (Osgood et al. 2007b).

4.3 Climatology, climate variability and forecasts in Southern Eastern Africa

In this section we analyze the main factors affecting African climatology - which are already part of the insurance contract design - and climate variability.

4.3.1 Monthly precipitation patterns and crop calendars

The climatology over a region - or the average weather over a period of about 30 years[7]- is determined by several dynamic and static factors depending on whether they evolve over time or not. The static factors include: latitude, altitude, surrounding orographic structure, proportion of land to water and proximity from water basins. Dynamic factors may evolve over time and are represented by vegetation coverage,

[7] Time scale accepted by the World Meteorological Organization.

podology (soil characteristics such as water retention), and marine currents. The seasonal climatology of African precipitation manifests itself as a zonally[8] symmetric band. This band, also called rainbelt, is located above the Equator in April, it moves northward in July then it moves back above the Equator in October and eventually shifts southward in January. This meridional migration of the rainbelt produces a single-peaked rainy season at the poleward edges of the tropical region while at latitudes closer to the equator, the rainy season season is double-peaked, with a dry season in winter, maxima in spring and fall, and a mid-summer break in between (Giannini et al. 2007).

The 9 villages under observation are located at different latitudes, thus present different yearly and monthly precipitation patterns. Fig 4.3 shows a map with the exact location of the villages. The three villages in Kenya - Eldoret, Kitale and Nakuru - are located on the Equator line, North-East of Lake Victoria, between 1300m and 2100m. The two villages in Tanzania, South-East of Lake Victoria are Babati (1350m) and Mbulu (1750m). Finally the four villages in Malawi are located at about -13 degrees south of the equator, at an altitude of about 1000m and include: Lilongwe, Chitedze, Kasungu and Nkhotakota.

Since the villages present different climatological seasonal cycles, their agriculture calendars also differ. Figures 4.4, 4.5, 4.6, and 4.7 present for each village (i) the monthly precipitation in (mm/day) calculated using the precipitation data provided by the Malawi, Kenya and Tanzania Meteorological Services; (ii) the agricultural calendar.

Malawi is located in Southern Africa, a predominantly semi-arid region with higher inter-annual rainfall variability and a pronounced seasonal cycle. The rainy season extends from October (November) to April (May). Rainfall distribution during the

[8]Zonally means that the climatic feature is the same for all longitudes in the same latitudinal band.

rainy season is quite variable; it depends on the interplay between tropical and mid latitude weather systems, as well as convective variability (Garanganga, 1998; Joubert and Hewitson, 1997). Rainfall in parts of Southern Africa exhibits also a preference for variability on the time scale of about two decades and it is related to variations in the Southern Hemisphere upper air circulation (Hasternath, 1991). The Tanzania villages present a similar precipitation bi-seasonal cycle with the rainy season that extends from November to May. On the other side, in Kenya the rainfall activity is concentrated in March-May and in September-December, the so-called long-rains and short-rains respectively (Hasternath, 1991). This pattern is quite accentuated for Kitale, while Eldoret present a precipitation peak in July-August.

Insurance contract calendars are based on information on crop growth phases. In figures 4.4, 4.5, 4.6, and 4.7, we present the maize agricultural calendars for each village, consistent with historical data and common planting schedules observed in the field. The crop growing period starts at the end of the sowing window (when seeds are cast over prepared ground) and it is structured in 3 growing phases: germination, tasseling and maturation. The time unit is the dekad - that is a 10 days period. The first dekad of each year goes from January 1^{st} to January 10^{th} [9], and each year is composed of 36 dekads The sowing window (in blue in the graphs) ends when the sowing conditions are met (in mm of precipitation/dekad), based on Famine Early Warning System Network (FEWS NET) and FAO criteria (following CRMG 2005). The sowing window for Kenya villages falls between March and April while for Malawi and Tanzania it falls between November and January. The growing period for Malawi lasts from January through Aril/May while for Kenya it lasts from March to August.

We explored the correlations between precipitation for the different growing seasons in the each village (Figure 4.1), to do so we calculated the cumulative precipita-

[9] The time unit for insurance contracts is also the dekad, however in this case, the first dekad corresponds to the first dekad of the first phase.

tion for each village during the respective growing seasons: January, February, March, April and May for Malawi and Tanzania; April, may June, July and August for Kenya.

	chitedze	kasungu	lilongwe	nkhotakota	babati	mbulu	kitale	eldoret	nakuru
chitedze	1								
kasungu	0.5597	1							
lilongwe	0.572	0.5137	1						
nkhotakota	0.3425	0.1816	0.1927	1					
babati	0.2495	0.2745	0.1374	0.3138	1				
mbulu	-0.0103	-0.0263	-0.0173	0.3801	0.6969	1			
kitale	0.0826	0.2638	0.2709	0.0435	-0.0138	-0.0619	1		
eldoret	-0.0711	0.0792	-0.0718	-0.035	0.1992	0.2259	0.6158	1	
nakuru	0.1603	0.0135	0.0981	0.1338	0.1108	0.1289	0.4855	0.316	1

Figure 4.1: Correlation between monthly precipitations for each village.

In figure 4.1 we distinguish chromatically the different regions: we use yellow for villages in Malawi, green for villages in Tanzania, and orange for villages in Kenya. Among the villages in Malawi, Chitedze presents a correlation of the order of 0.6 with Kasungu and Lilongwe, while Nkhotakota presents a very low correlation (0.2) with the other villages. A possible explanation is that Nkhotakota is a bit closer to Lake Malawi, thus it is likely to be characterized by higher humidity and different precipitation patterns with respect to the other villages in Malawi. Among the villages in Tanzania, Mbulu and Babati show a correlation of the order of 0.69. Among the villages in Kenya, Kitale and Eldoret have a correlation of 0.6 while the correlation between Nakuru, Kitale and Eldoret are lower, respectively 0.48 and 0.31. From the table we can also examine the correlation between different regions: precipitation in Tanzania and Malawi villages do not appear to be very strong (almost zero except for Babati), with Nkhotakota showing the higher correlations; correlations between Kenya and Malawi villages are very low and often negligeable; the same can be said for correlations between Kenya and Tanzania villages.

As we could have expected, correlations between villages within the same region are positive (even if not particularly strong). The very low correlations (practically zero) between most villages in Malawi and Tanzania, as well as between villages in Malawi and Kenya might open opportunities for re-insurance schemes between these regions. In the next section we will perform further analysis on precipitation patterns by examining the signature of climate variability.

4.3.2 Climate variability and ENSO

Climate variability needs to be taken into account to understand the precipitation patterns in the regions under examination; we will focus in particular on ENSO. ENSO signals, generated in the Pacific basin, are an important factor in determining inter-annual precipitation variability in Southern and Eastern Africa both directly via an atmospheric bridge - *atmospheric teleconnection* - (Glantz et al. 1991; Wallace et al. 1998) and indirectly, via the response of the Indian and the Atlantic Oceans (Klein et al. 1999; Alexander et al. 2002). In this section (i) we examine the precipitation associated to each village with respect to the results of a study by Giannini et al (2007) investigating climate variability; and (ii) we inspect the rainfall patterns and the correlations between villages for different ENSO states.

Principal Component Analysis

In order to relate the precipitation patterns in the villages under examination to more global climatology patterns, we compare our data with the main components of the PCA analysis performed at the continental scale by Giannini et al. (2007). Principal component analysis (PCA) involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called *principal components*. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. By maximizing the variance captured in the first pattern (component), and in subsequent orthogonal, or independent, patterns, PCA identifies broad spatial features, allowing one to summarize a large fraction of the information.

In their study, Giannini et al. use Principal Component Analysis (PCA) to identify patterns of African climate variability at the continental scale, followed by linear regression to connect these patterns to common, global-scale forcings. In their analysis, PCA identifies spatial patterns that express co-variability in time across the tropical African gridded precipitation dataset produced by the Climatic Research Unit of the University of East Anglia (CRU, Hulme1992). They apply PCA to annual-mean (July-June) precipitation anomalies, with respect to the long-term mean, in the domain between $35°S$ and $30°N$, $20°W$ and $60°E$. They apply linear regression to relate the temporal variability associated with the spatial patterns identified by PCA to other aspects of the global ocean-atmosphere system.

We reproduce in figure 4.8 principal component analysis figures and caption from Giannini et al. (2007), figure 4.8 (top row) presents the three main patterns - that combined capture 37% of the total variance in precipitation over the tropical African domain considered. The first pattern in the top row (the leading pattern, that we will call pattern a) is a continent wide drying trend, followed by the two patterns that capture the influence of the ENSO (second and third figure in the top row, we will refer to them as pattern b and c respectively). Pattern a is statistically related to the global SSTs, with the sign such that drying over Africa is associated with warmer tropical Pacific, Indian and South Atlantic Oceans, and a cooler North Atlantic Basin (Figure 4.8 g, first image in bottom row).

Pattern b represents the *canonical* ENSO influence, one that combines the effects of remote, or tropical Pacific, and local, especially Indian Ocean, surface temperatures (Figure 4.8 *h*). It captures the wetter than average conditions over eastern equatorial Africa known to be a maximum during the October-December short rains, which coincide with mature warm ENSO conditions, as well as the drier than average conditions over southern Africa known to be most prominent in the January-March season immediately subsequent to the mature phase (Figure 4.8 *b*). The Indian Ocean Seas Surface Temperature (SST) anomalies associated with the dipolar rainfall pattern between eastern equatorial and southern Africa are related in part to ENSO. Due to their thermal inertia, the remote tropical oceans warm in response to the ENSO-induced changes in the tropospheric temperature with a lag of a few months (see, e.g. Klein et al. 1999; Chiang and Sobel 2002; Sobel et al. 2002; Chiang and Lintner 2005).

Pattern *c* (Figure 4.8 *c*) captures the pure atmospheric influence of ENSO and it results stronger in eastern Africa. A warm ENSO can induce below-average precipitation in eastern equatorial Africa when the atmospheric bridge dominates (as depicted in the third pattern) or it can result in above-average precipitation, when the dynamically-induced Indian Ocean response overwhelms the remote atmospheric effect (as in the second pattern). Eastern equatorial and southern African averages are correlated with both drying and ENSO patterns (with correlations of the order of 0.5). ENSO is found to be the dominant influence on the predictable component of interannual rainfall variability in eastern equatorial and southern Africa (Giannini et al. 2007).

We examined the correlation between the precipitation for each village and the time series associated to the three main components detected by Giannini et al. in the attempt to detect the main sources of climate variability affecting the precipitation patterns for the 9 villages. The results reported in figure 4.9 indicate that: (i) the

Malawi villages present a positive correlation of the order of about 0.4 with the third component (pure atmospheric ENSO influence); (ii) the Tanzania villages show a positive correlation with the first component, of the order of 0.5; (iii) the Kenya villages also show a positive correlation with the first component, of the order of 0.6 for Kitale and Eldoret and only 0.26 for Nakuru. These results seem to suggest that only the Malawi villages are primarily correlated with the ENSO signal.

ENSO-related variability (patterns *b* and *c*) is associated to events that recur every 2 to 7 years. The first component (pattern a) statistically related to the global SSTs is associated to a longer time scale. For weather-index insurance and re-insurance it is interesting to take into account both the general trend of increasing SST and the shorter-term ENSO related variability. In the remaining part of this section we will focus on the latter.

ENSO

Once developed in the Pacific Ocean, El Niño and La Niña shift temperature and precipitation patterns in many different regions of the world. Weather patterns associated to each ENSO states are quite consistent over time. Changes in atmospheric circulation induced by El Niño (or La Niña) produce repeated climatic outcomes even in regions remote from the Pacific, directly via atmospheric teleconnections and indirectly affecting sea surface temperatures (SSTs) in other ocean basins[10]. In the case of Eastern and Southern Africa, changes in rainfall are due to changes in the Indian Ocean temperatures, which warm or cool consistently with the tropical Pacific (El Niño/La Niña) (Goddard and Graham, 1999). These shifts, although varying somewhat from one El Niño to the next, are fairly consistent in the regions shaded on the map below. ENSO's influence over Southern African rainfall is strongest in the

[10] The IRI ENSO online resources to provide a comprehensive overview of the ENSO phenomenon and its global effects: http://iri.columbia.edu/climate/ENSO/globalimpact/

peak austral summer months (December-March), when the event has reached maturity and the Inter Tropical Convergence Zone is furthest south (Mason, 1996; Clay, 2003). Ropelewski and Halpert (1987, 1989) suggested two areas of ENSO related precipitation effects: equatorial eastern Africa (which includes Kenya and Tanzania) and south-eastern Africa (including Malawi).

Figure 4.2[11] clearly shows this bipolar precipitation pattern: la Niña events are associated with dry climate in eastern Africa and wet climate in Southern Africa. In other words, la Niña phase (also called Cold Episode) increases the likelihood for stronger and more frequent storms in Southern Africa, and is thus associated with an increased probability for above normal rainfall in that season. During El Niño (or Warm Episode) the precipitation dipole is inverted (Halpert and Ropelewski, 1992).

Climate variability associated to ENSO

Given the important role played by ENSO in determining Eastern and Southern Africa climate variability we further explore the relationship between precipitation patterns and ENSO signature. We adopted the index NIÑO3.4 to attribute an ENSO state to each year from 1960 to 2006; we then analyzed the precipitation patterns associated to each village for different ENSO states (El Niño, La Niña and Neutral years). The index NIÑO3.4 is defined as a three-month running average of sea surface temperature (SST) departures from normal for a critical region of the equatorial Pacific. The Niño 3.4 region is delimited by the following latitude and longitudes: $120°W - 170°W$, $5°N - 5°S$, this region is displayed in 4.10. El Niño event is then identified if the 3-month running-average of the NIÑO 3.4 Index exceeds $+0.5°C$ ($-0.5°C$ for La Niña) during the period October - December.

The SST data used to calculate he index NIÑO 3.4 is the NOAA Extended Re-

[11] Available at: http://iri.columbia.edu/climate/ENSO/globalimpact/temp_precip/region_elnino.html

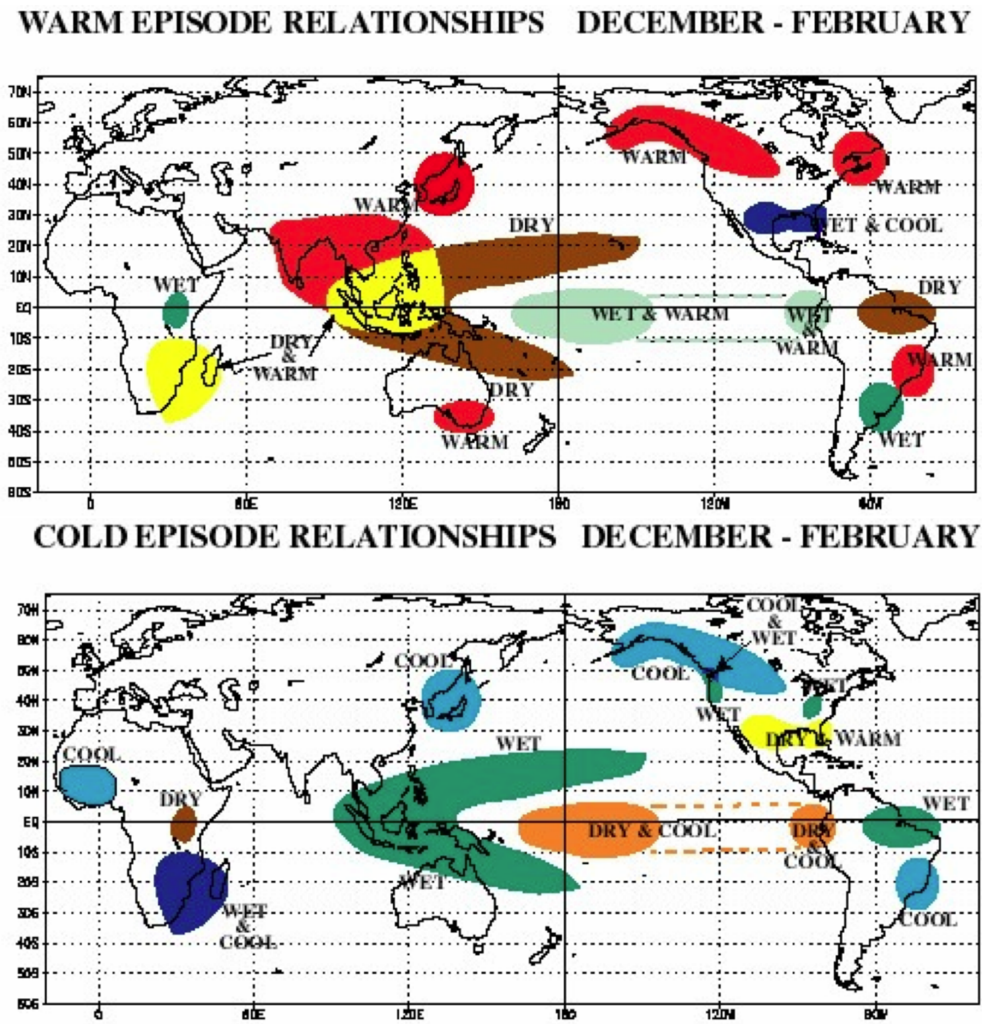


Figure 4.2: Global teleconnections of (a) El Niño and (b) la Niña episodes Warm Episode Relationship, Dec-Feb (Halpert and Ropelewski, 1992).

constructed Sea Surface Temperature (ERSST) version 2[12].

[12]The ERSST was constructed using the most recently available International Comprehensive Ocean-Atmosphere Data Set (ICOADS) SST data and improved statistical methods that allow stable reconstruction using sparse data. This monthly analysis begins January 1854, but because of sparse data the analyzed signal is heavily damped before 1880. Afterwards the strength of the signal is more consistent over time. The ERSST version 2 (ERSST.v2) is an improved extended reconstruction; this means that the high-frequency SST anomalies are reconstructed by fitting to a set of spatial modes. Compared to the earlier reconstruction, version 1 (v1), the improved reconstruction better resolves variations in weak-variance regions. It also uses sea-ice concentrations to improve the high-latitude SST analysis, a modified historical bias correction for the 1939-1941 period, and it includes an improved error estimate. For more details:

From now on, we will indicate the ENSO state associated to the period October-December of the year before the harvest as $ENSO^{-1}$ and the ENSO state associated to the period October-December of the harvest year as $ENSO^{0}$. We then calculated the monthly average cumulative precipitation for each station differentiating years by ENSO state; we used the $ENSO^{-1}$ state for Malawi and Tanzania and the $ENSO^{0}$ state for Kenya. The reason why we picked the signal in the previous year for Malawi and Tanzania is that the growth period in these regions is December-April, which is likely to be more affected by the ENSO state immediately preceding the sowing phase. The results are presented in the histograms in figures 4.11, 4.12, and 4.13. Niño+ (Niña+) indicates a strong El Niño (La Niña) state with index NIÑO3.4 $\geq 1°C (\leq -1°C)$. Niño (Niña) indicates El Niño (La Niña) state with NIÑO3.4$\geq 0.5°C$ $(\leq -0.5°C)$. Based on the ENSO patterns presented in figure 4.2 described by Halpert and Ropelewski, (1992):

- We expected higher (lower) precipitation in Malawi villages in years preceded by ENSO-1 equal to La Niña (El Niño) both strong and regular - Niña+ and Niña respectively. These patterns were confirmed by our results especially for the first 4 moths of the year (January to April) that correspond to the growing season. The village of Nkhotakota represents the only exception as it does not show any clear pattern.

- For the Tanzanian villages we expected the opposite, that is: lower (higher) precipitation in years preceded by $ENSO^{-1}$ equal to La Niña (El Niño). Our expectations for Tanzania villages are partially met: precipitation seem to be higher in El Niño years, however we cannot detect a very clear pattern.

- For Kenya we expected lower precipitation when the $ENSO^{=}$corresponds to La Niña; unfortunately the results relative to the crops' growing period (April to

http://www.ncdc.noaa.gov/oa/climate/research/sst/sst.html

August) do not show a clear trend which suggests that ENSO is only one of the factors affecting precipitation.

We estimated correlations between cumulative precipitation for each village during the respective growing seasons: January, February, March, April and May for Malawi and Tanzania; April, may June, July and August for Kenya. It is important to stress that in some cases these correlations tables concern only 3 or 4 observations, thus we need to be cautious in our interpretation. It is interesting to note that precipitation in villages in Malawi and Tanzania show, in general negative or no correlation when $ENSO^{-1}$ is neutral (SST anomaly between +/- 0.5 deg C), the only exception is represented by Nkhotakota in Malawi, which shows atypical trends and whose precipitation show positive correlations with the Tanzanian Villages. The correlation becomes predominantly positive (neutral for Nkhotakota) if the $ENSO^{-1}$ corresponds to strong La Niña. However, for years preceded by strong El Niño the correlation patterns become more ambiguous.

Correlations between precipitation in Malawi and Kenya villages are not very strong when we consider all years. Once we select years according to the ENSO state, we observe:

- strong positive correlations if $ENSO^{-1}$ is El Niño (except for Nkhotakota-Malawi and Eldoret-Kenya)
- Nkhotakota and Eldoret show positive correlations with both Kenya and Malawi villages if $ENSO^{-1}$ is a La Niña.

Kenya and Tanzania villages do not present a very clear relationship, in general we observe:

- positive correlations if $ENSO^{-1}$ is La Niña.

- negative correlation if $ENSO^{-1}$ is El Niño.

The relationships just described suggest a high level of complexity in the precipitation patterns with respect to ENSO.

4.3.3 Climate Forecasts

Models can now predict ENSO up to a year in advance; according to a study by Mason (1998) by using ENSO, predictions for southern African rainfall may be made for lead times of up to five months, with a high degree of confidence. Goddard and Dilley (2004) note that during El Niño and La Niña events climate forecasts are shown to be more accurate. Stronger ENSO events lead to greater predictability of the climate and, potentially, the socioeconomic outcomes. Thus, the prudent use of climate forecasts could mitigate adverse impacts and lead instead to increased beneficial impacts, which could transform years of ENSO extremes into the least costly to life and property.

4.4 Analyses of contracts

We want to study the statistical properties of the insurance contracts taking into account climate variability and looking for opportunities for re-insurance schemes. The question we are trying to answer is: are there possibilities for re-insurance using geographic diversification? In this section: (i) we calculate the possible payouts that we would obtain using historical precipitation data for each village; (ii) given the relatively short precipitation time series available, we extrapolate precipitation distributions for each village using Monte Carlo simulation. More specifically, we model precipitation by a gamma distribution the parameters of which are deducted from the historical precipitation. The Monte Carlo approach allows us then to extract large random samples from the precipitation distribution. The purpose of the exercise is to analyze the statistical distribution of payouts using a larger sample of precipitation data.

First, we use the historical precipitation data to calculate the payouts for rainfall patterns associated to different ENSO states. Then, while performing the Monte Carlo simulations, we calculate mean and variance of contracts payouts for precipitation distributions associated to different ENSO states.

Before presenting our analysis, it is important to point out a few caveats. First, in the Monte Carlo simulation we adopt the gamma distribution to model precipitation in the regions under examinations. The choice of gamma distribution is a strong assumption supported by previous literature (Mearns, L.O. et al. 1997). Second, the precipitation data used for the Monte Carlo simulations represent relatively short time series (20 to 40 years depending on the village considered). Third, the contract used in the Monte Carlo simulation have been slightly simplified with respect to the real contracts: in order to perform the simulation, we assumed that the beginning of the sowing season is the same every year, in reality the sowing phase varies according to the sowing conditions (i.e. humidity in the ground). Finally, climatologist have established a highly significant relationship between ENSO and inter-annual rainfall variations in Southern Africa, however this relationship is quite complex: not every El Niño event brings low rainfall, vice versa low precipitation are not necessarily related to El Niño. In our simulation of historical payouts we try to capture interannual variability based on the ENSO index Niño 3.4. More sophisticated forecasts need to be developed and integrated to the insurance scheme in order to better reflect the complexity of the climate system; this is part of our future research plan

4.4.1 Historical payouts analysis and variability

For each village we perform the following three step analysis. First, we use the historical rainfall data available during the period from 1960 to 2006 to calculate the insurance payouts as if the 2006 maize contracts for each village were applied over that period. The insurance contracts used in this exercise cover one acre of hybrid maize production using the prices, parameters, and constraints agreed to by the stakeholders during the 2006-07 season. The packages actually implemented in the 2006 pilot scheme in Malawi included a bundle of groundnut and maize, however in order to get non-ambiguous results, the contract used in this exercise covers only one crop, maize. Maize was selected because it is highly sensitive to water stress, and the varieties available in Malawi have been relatively well characterized for agronomic modeling.

Second, using the formulas applied in the 2006 implementation we calculate the "historical burn" insurance price appropriate for each ENSO phase. Historical burn pricing is performed by relying entirely on payouts determined from historical data, without attempting to characterize the underlying distributions[13]. The insurance price (the premium) is equal to Average(payout) + Loading * (Value at Risk -Average(Payout)). We apply here the pricing utilized in the design work of the 2006 insurance. We calculate here two insurance prices with loading equal to 6% and 6.5%.

Third, we refine our analysis taking into account the different ENSO states. As explained in the section 3 we define the ENSO state (El Niño, La Niña, and Neutral) based on the index NIÑO3.4. As mentioned in our previous discussion, an important constraint is represented by the small number of years available for analysis.

[13] Although this technique may be overly simplistic, it was utilized here for two reasons. First, it is highly transparent, because it does not require specification of distributional assumptions (except that the set of historical draws characterizes the entire distribution). Second, it was the pricing method used for determining the official price of the Malawi insurance (Dan Osgood's personal communication).

Results for this section are presented in figures 4.14, 4.15, and 4.16 which is composed of three sections: figure 4.14 is preceded by a comprehensive legend and presents the results for Malawi, figure 4.15 the results for Kenya, and figure 4.16 the results for Tanzania. For each village we provide two tables and a graph. The first table corresponds to the three-step analysis described above; the second table will be discussed in section 5. The graphs underneath the tables show the magnitudes of payouts for each year; in the graph the ENSO state corresponding to every payout is indicated chromatically: pink for La Niña, blue for El Niño, green for neutral years.

ENSO impact for Malawi – The calculations for each village are presented in figure 4.14. The average payouts in El Niño phases are substantially higher than average. The average payouts in La Niña years are much lower than average (average corresponds to the column“all”) for Lilongwe, Chitedze and Kasungu. Nkhotakota does not show these dramatic differences, however the average payouts in El Niño years is still higher than in La Niña years.

ENSO impact for Kenya – The villages of Eldoret and Kitale present responses similar to the Malawi villages: lower average payouts and insurance rate in La Niña years with respect to an average year (no distinction between ENSO states). The village of Nakuru, surprisingly shows lower average payouts and insurance rate in Neutral years (Fig. 4.15).

ENSO impact for Tanzania – The contracts for Babati and Mbulu respond in the opposite way with respect to the Malawi villages: we observe average payouts and insurance rate in El Niño years substantially lower than average (Fig. 4.16).

4.4.2 Monte Carlo Simulations

Precipitation time series are surprisingly long for Malawi but they are still quite short for our research purposes and might represent a serious shortcoming in our analysis.

For this reason, we adopt Monte Carlo methods on the available precipitation data to extrapolate the precipitation distributions. The Monte Carlo approach consists in modeling a quantity of interest (here the precipitation) by a probability distribution (here a gamma distribution) and then performing random sampling from this distribution[14].

First, we separated the precipitation data for each growing season by phase[15] and by ENSO state. Second, we calculated the gamma distribution parameters for each set of precipitation data. Third, we extracted samples of 1000 elements from the precipitation pdf's; since each growing season includes 3 phases we got 3 samples of 1000 elements per village. Fourth, for each sample, we calculated the corresponding payouts and then we calculated the total payouts (sum of payouts of the three phases). Fifth, we calculated mean and variance for each sample. The results are presented in figures 4.17, 4.18, and 4.19. For each village, we provide a table showing: the mean payouts by phase and the mean total payouts for different ENSO states. The results are also summarized by histograms under each table.

Our calculations indicate that mean payouts are higher in El Niño years for villages in Kenya while they are higher in la Niña years for villages in Tanzania. Malawi villages present more ambiguous results. For Nhotakota we observe higher payouts in la Niña years, for Chitedze higher payouts in El Niño years, and for Lilongwe and Kasungu we observe higher payouts in neutral years. The Monte Carlo simulation results confirm the historical payouts for Kenya and Tanzania but not for Malawi. One possible explanation is that in calculating the historical payouts we took into account the historical end of the crop sowing phase which corresponds to the"beginning of the growing period" and varies from year to year, while in the Monte Carlo analysis we simplified the contracts imposing the same starting date for all years. This reduced

[14]Random sampling from a probability distribution is always possible when the distribution function F is known: one can draw a number x uniformly at random in $[0, 1]$ and output $F^{-1}(x)$.

[15]Each growing season is composed by 3 phases: germination, tasseling and maturation.

flexibility of the starting date might have affected the final payouts for Malawi where precipitation are scarcer than in Kenya and Tanzania.

4.5 Possibilities for re-insurance?

In this paper we presented the first steps of a broader research project whose goal is to develop a re-insurance scheme built on climate forecasts, and based on anti-correlated or independent precipitation patterns.

In sections 3, we analyzed the precipitation patterns of the regions under examination, at the village scale. In order to relate the precipitation patterns for each village to more global climatological patterns we compared our data with the main components of the PCA analysis performed at the continental scale by Giannini et al. (2007). Correlation results seem to suggest that precipitation in Malawi villages are affected by the ENSO signal, while precipitation in Kenya and Tanzania villages are mostly associated to a continental drying trend related to global SST.

In sections 4, we studied the statistical properties of the insurance contracts taking into account climate variability. First, we used the historical precipitation data to calculate the payouts for rainfall patterns associated to different ENSO states. Then, while performing the Monte Carlo simulations, we calculate mean and variance of contracts payouts for precipitation distributions associated to different ENSO states.

The results obtained from historical precipitation data indicate that more abundant rainfalls reduce payouts and the risk of loan default during La Niña in Kenya and Malawi, during El Niño in Tanzania. The results of the Monte Carlo simulations confirm our findings for Kenya and Tanzania but not for Malawi.

4.5.1 Contract pricing and opportunities for reinsurance integrating the ENSO signal.

In the current Malawi scheme, price is independent from climate forecast (ENSO state for instance), banks impose the constraint that the loan plus interest should be equal to the maximum liability of the insurance, and farmers obtain a loan for inputs that suffice just for cultivating one acre of land. This set-up is kept constant across seasons regardless of what seasonal forecasts say. According to focus groups and to a household survey, a majority of farmers were interested in larger loans; in fact, most participating farmers own at least four acres (Osgood et al. 2007a). As suggested by Phillips et al (2002), a rational mean of avoiding losses and benefiting from opportunities would be to decrease the area planted in years with expected rainfalls below normal, and to increase the area when rainfall is expected to be optimal for yields.

An interesting experiment is to consider contracts whose price varies according to the ENSO forecast. Note that the contract price is the sum of two terms: the average expected payout, plus a term representing the value at risk (refer to section 4 for the formula). We calculated the contract prices for different ENSO states based on historical precipitation data; both the mean payout and the value at risk can vary with the ENSO state. The results are presented in figures 4.14, 4.15, and 4.16 (in the first table for each village). For instance, the analysis for Malawi shows that as the maximum liability (the limit of coverage provided by an insurance policy) of the insurance remains constant (does not depend on the ENSO state) the insurance rate decreases in La Niña years because of a decrease in premium (price of the insurance). In other words: with a constant amount of money for premium, the maximum liability of the insurance contract could be increased if the contract actually reflected the changing nature of drought risk. This way the farmers could be allowed to cultivate larger areas in favorable years. Similar conclusions could be drown for Kenya (La Niña years are favorable) and Tanzania (El Niño years are favorable). The insurance rate can differ substantially across ENSO phases. For instance, for Malawi the prices appropriate for La Niña phases are in general almost an order of magnitude lower than the prices appropriate for El Niño phases.

Also, since ENSO patterns are forecastable, these insurance products could include also a mitigation component aimed at promoting land management practices modulated on forecasts and aimed at reducing losses.

Osgood et al. (2007a, b) explore the potential for another scheme where: (i) the input mix (proportion of high-yield maize seed and fertilizer) remains constant across seasons, (ii) the insurance price (premium) remains also fixed in every ENSO state, (iii) only the maximum liability changes adjusting insurance rate to ENSO (Max Liability = Premium / Insurance rate). As a consequence, the respective loan size and budget for inputs change too. In theory, modifying the loan would be like modifying the total area cultivated with high-yield inputs provided by the bundled loan-insurance contract. For instance, for Malawi when La Niña conditions anticipate low chance of drought, farmers receive more inputs and can therefore cultivate more land with the hybrid seeds and fertilizer provided by the scheme. When El Niño indicates high risk of crop failure, the inputs given to farmers will be less.

We tested this scheme for all villages based on historical precipitation data. In Figures 4.14, 4.15, 4.16 the second table for each village presents the results of this exercise: the elements of a package where the insurance rate is adjusted according to ENSO phase. The Input Budget (IB) is the budget available for inputs and the Input Budget Weight is the ratio of IB in different ENSO phases to the IB of the non-ENSO-adjusted package. In Malawi, holding the insurance price constant, the changing ratio between price and insurance rate leads to a maximum liability in La

Niña years that is much higher than in other years. The figures indicate a budget available for inputs in a La Niña year larger (much larger for Kasungu and Chitedze) than in the non-ENSO-adjusted package (4.14). We observe the same for two villages in Kenya: Eldoret and Kitale. Nakuru in Kenya presents an anomalous response with higher maximum liability and higher IB in"neutral years' (4.15). Finally in Tanzania maximum liability and IB are higher in El Niño years (4.16).

4.5.2 Limits and Perspectives

We based our analysis on a number of simplifying assumptions - such as using a fixed contract starting date in the Monte Carlo approach - that will be reconsidered in future work. Second, the model used a single-crop contract; future research should test multi-crop contracts possibly combining crops with different responses to droughts. Third, ENSO phenomenon is just one factor affecting seasonal rainfall in southern Africa and more sophisticated seasonal forecasts should be integrated into the index insurance scheme in order to improve the reliability of the model.

We have not explored in detail the possible combined effects of ENSO and climate change on southern Africa (Mason, 2001). In particular, the role of the Indian Ocean deserves further attention. In their analysis, Giannini et al. point out two possible non mutually exclusive explanations for the drying signal (pattern a of the PCA) in southeastern Africa: (i) the warming trend in the Indian Ocean (Hoerling et al. 2006), which is understood to enhance the drying impact of warm ENSO events on this region (Richard et al. 2000); (ii) global warming that is considered the cause for the recent trend towards more frequent and persistent warm ENSO events (Timmermann et al. 1999, Trenberth and Hoar 1997), thus affecting Southern African rainfall indirectly. There is still a large debate on this matter.

Despite these limitations, our preliminary results suggest that regional pooling of risk based on diverse climatic patterns seems to be a viable proposition. By integrating forecasts in multi-year contracts, these insurance products might also include forecast-based land-use guidelines to mitigate losses. From this case study three aspects emerge as precondition to possible regional insurance and reinsurance schemes: the need for regional/supranational coordination; private-public partnership between governments and insurance companies to maximize insurance penetration in rural areas; and product design robustly rooted in scientific research.

The next step in our research plan will focus on possible re-insurance schemes designed to exploit the anti-correlation patterns related to interannual climate variability for different regions in Africa. Re-insurance schemes based on forecasts could have important implications for adaptation to climate change in Southern Africa by reducing farmers' long-term vulnerability to droughts. Also, they could be exported to other regions where the ENSO signature is strong and shows diverse patterns, such as Latin America.

Figure 4.3: Village locations

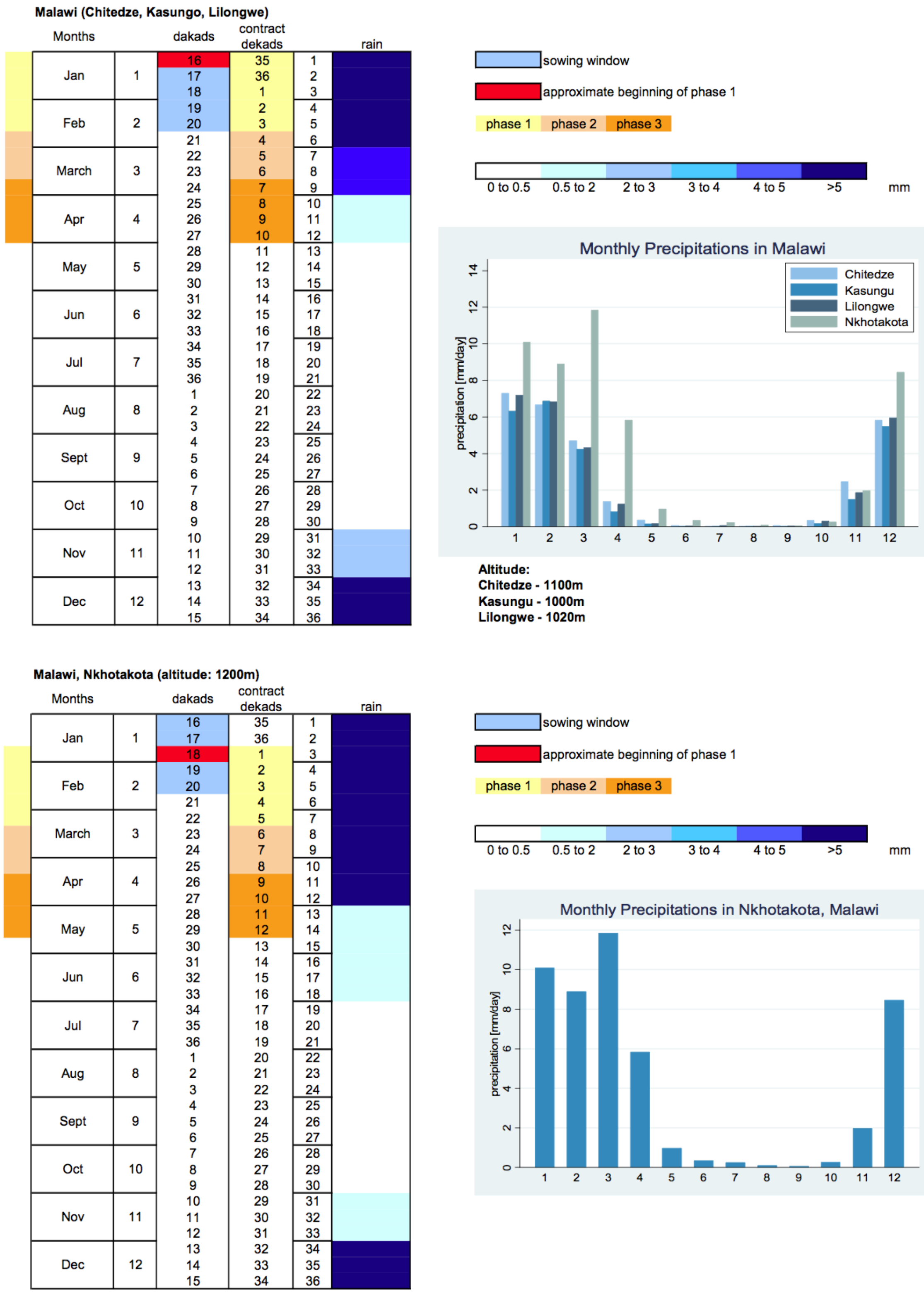


Figure 4.4: Agricultural Calendars and Precipitation Data for Villages in Malawi.

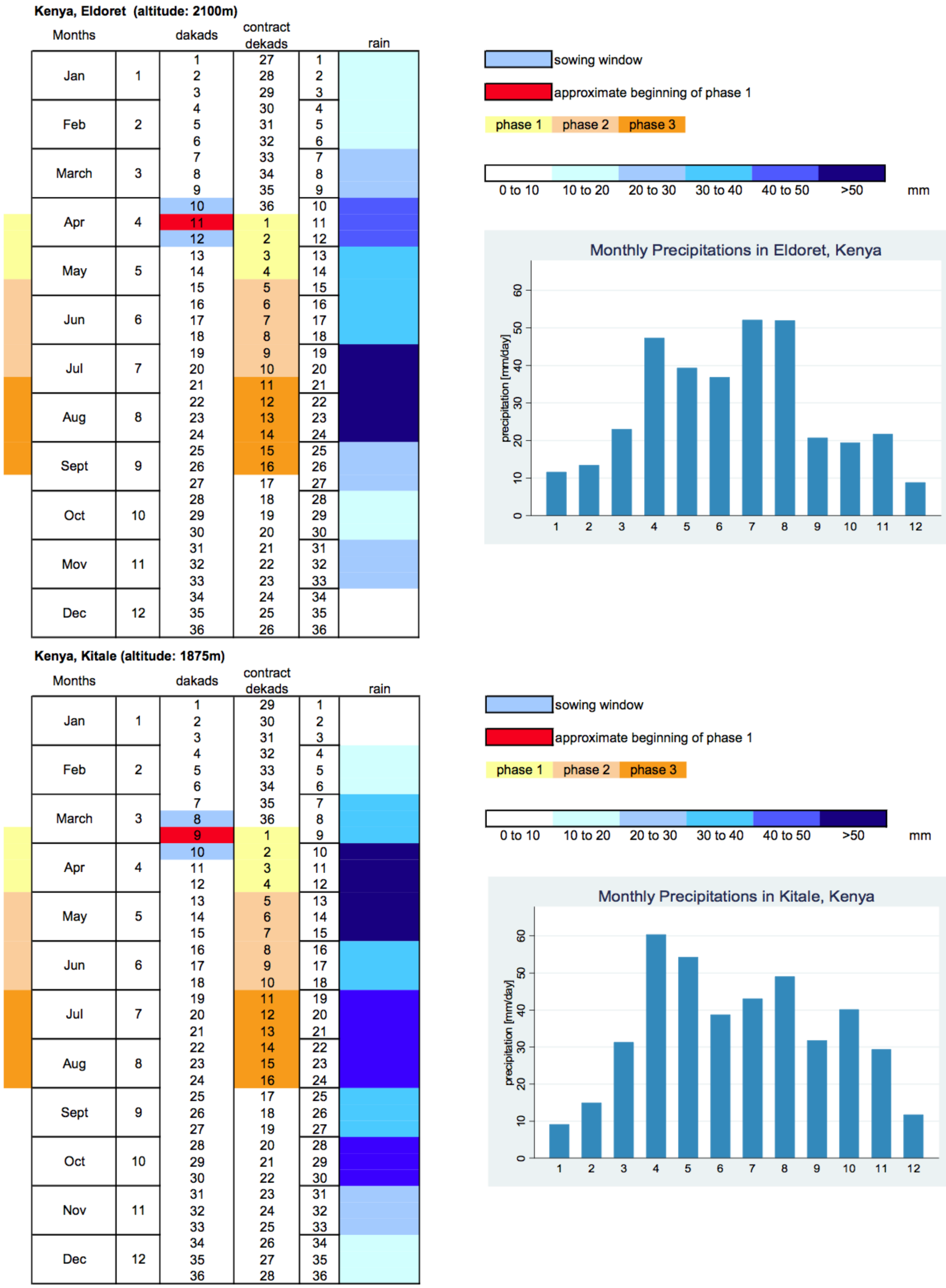


Figure 4.5: Agricultural Calendars and Precipitation Data for Villages in Kenya.

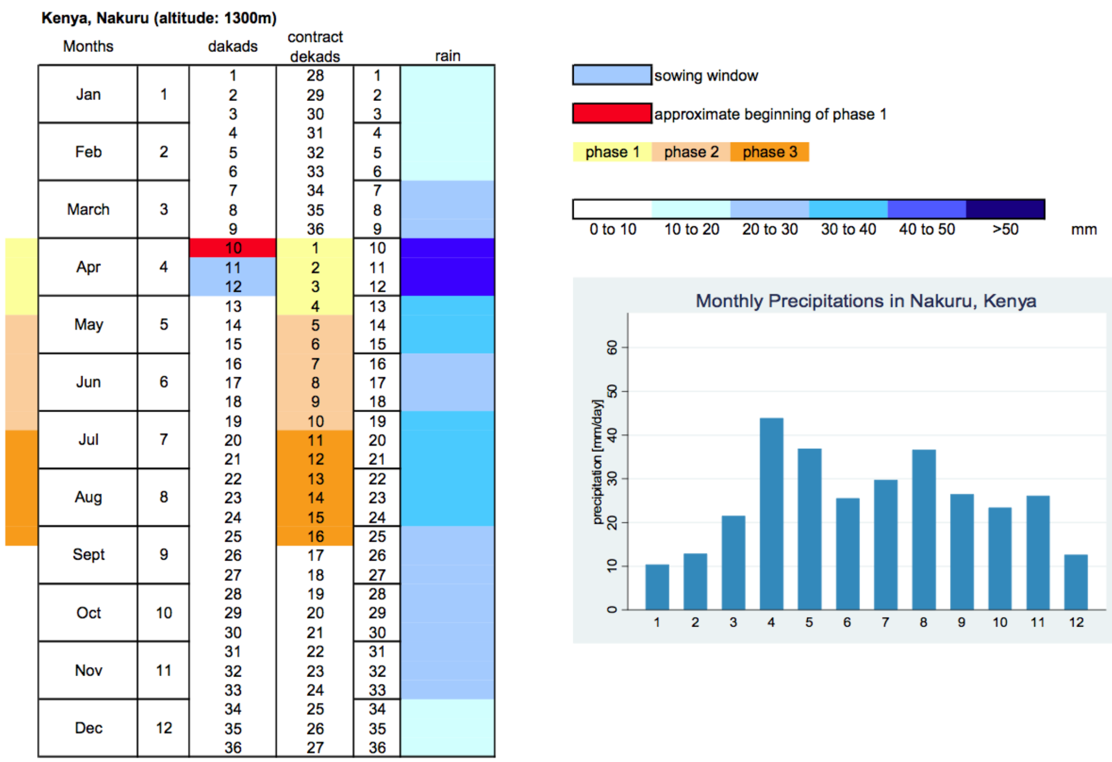


Figure 4.6: Agricultural Calendars and Precipitation Data for Villages in Kenya (continued).

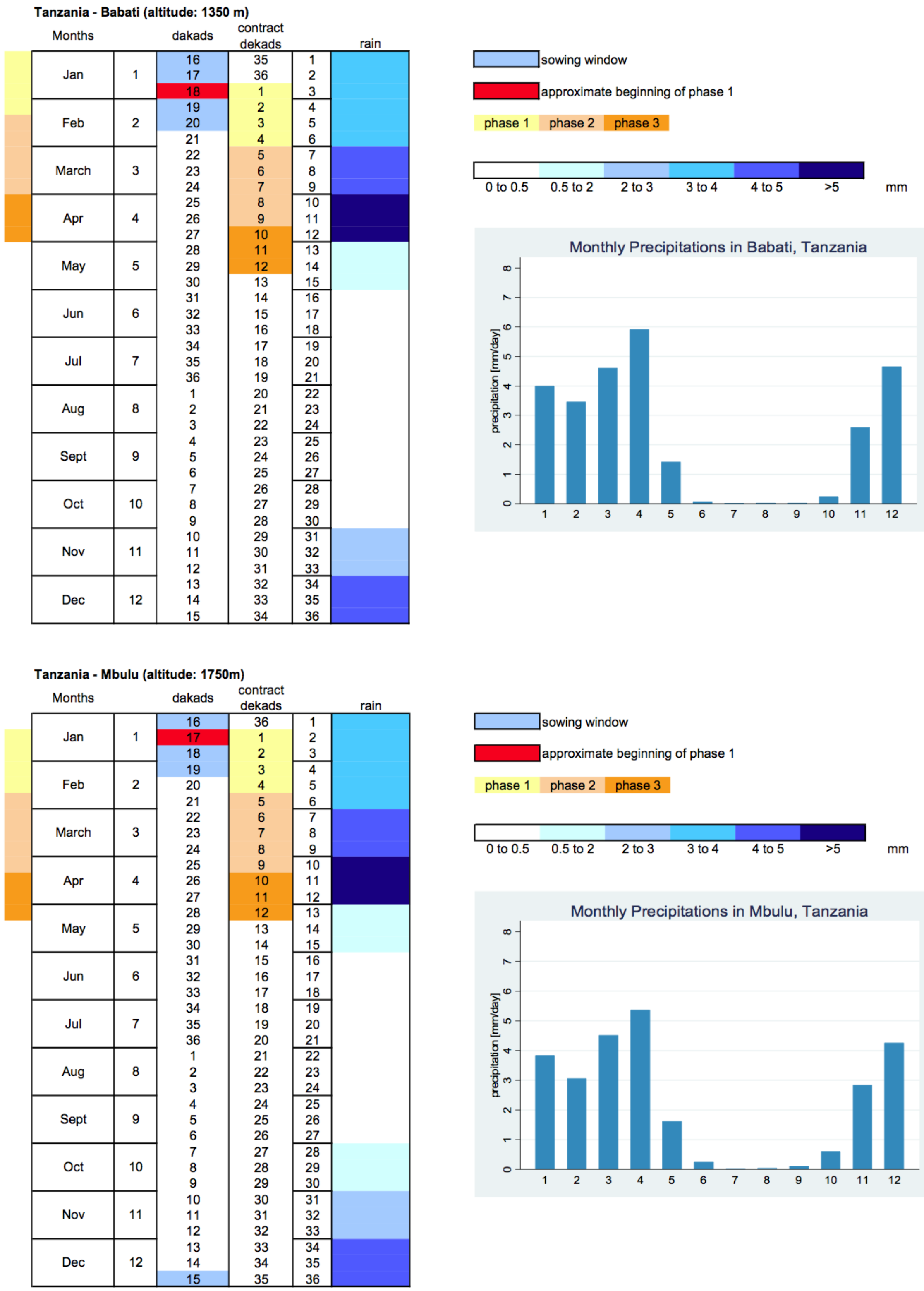


Figure 4.7: Agricultural Calendars and Precipitation Data for Villages in Tanzania.

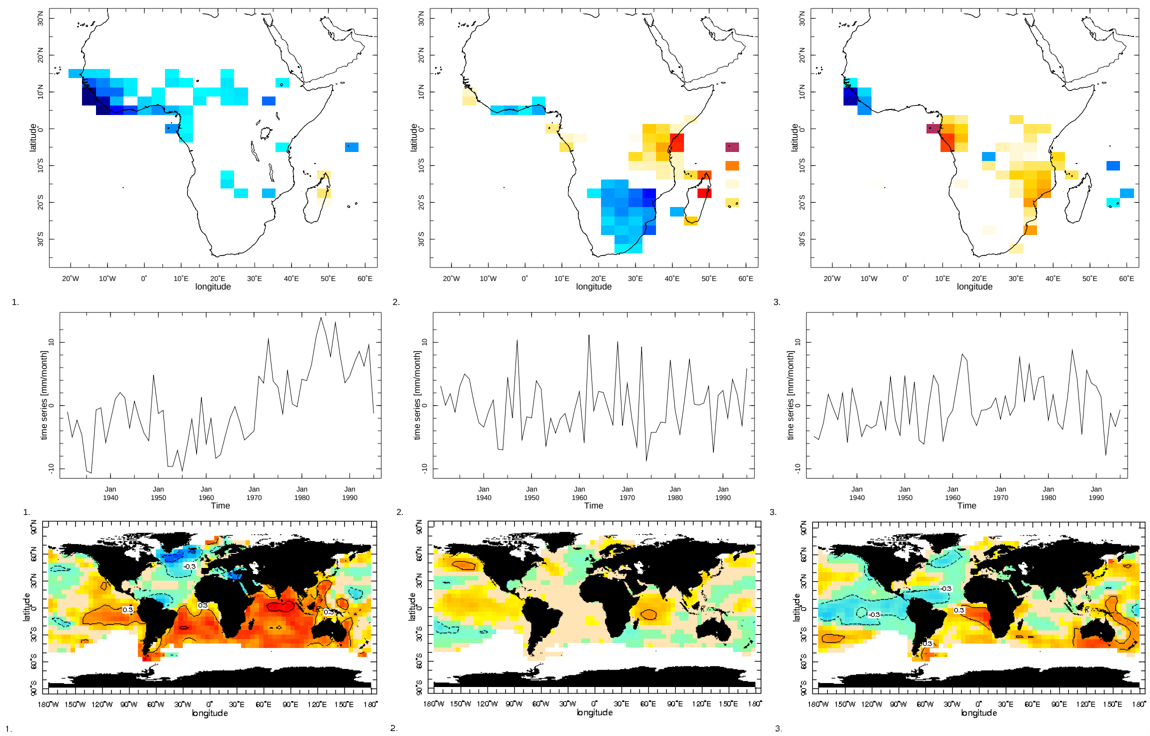


Figure 4.8: The three leading patterns of a Principal Component Analysis performed by Giannini et al. (2007) on annual mean (July-June) precipitation over Africa during 1930-1995: Top row, figures a, b, c: The spatial patterns, obtained by linear regression of the time series in d, e, f onto precipitation - anomalies are in color, in mm/month, while the contours delimit regions where regression is statistically significant at the 5% level. Middle row, figures d, e, f: The associated time series (in units of standard deviation). Note that the upward trend in (d) indicates increasingly stronger values of the negative anomalies in the pattern in (a), i.e. a drying trend. Bottom row, figures g, h, i: Regression patterns of the time series in d, e, f with sea surface temperature (Kaplan et al. 1998). Anomalies are in contour, spaced every 0.05 deg C, and dashed in the case of negative values; the presence of color represents their statistical significance at a level of 5% or higher.

Malawi

	chit	kas	lil	nkh	sdv_1	sdv_2	sdv_3
chit	1.0000						
kas	0.3886	1.0000					
lil	0.5734	0.4140	1.0000				
nkh	0.4433	0.3409	0.2864	1.0000			
sdv_1	-0.0067	-0.0059	-0.0916	-0.3364	1.0000		
sdv_2	-0.3638	-0.0295	-0.1384	-0.2609	-0.0952	1.0000	
sdv_3	0.4944	0.3227	0.4166	0.4046	-0.2493	-0.2260	1.0000

Tanzania

	bab	mbu	sdv_1	sdv_2	sdv_3
bab	1.0000				
mbu	0.8646	1.0000			
sdv_1	0.4797	0.5587	1.0000		
sdv_2	-0.0133	-0.0674	-0.0952	1.0000	
sdv_3	0.1390	0.0342	-0.2493	-0.2260	1.0000

Kenya

	kit	eld	nak	sdv_1	sdv_2	sdv_3
kit	1.0000					
eld	0.6368	1.0000				
nak	0.1420	0.3690	1.0000			
sdv_1	0.6121	0.6804	0.2648	1.0000		
sdv_2	0.1461	-0.0511	-0.1151	-0.0952	1.0000	
sdv_3	-0.1737	-0.0904	-0.1703	-0.2493	-0.2260	1.0000

Figure 4.9: Correlation between average cumulative yearly precipitations for each village and the three main climate patterns (sdv1, sdv2, sdv3) obtained by Giannini et al (2007) performing Principal Component Analysis (in fig.1 bottom row) over the period 1930-1995. Data used by Giannini et al. (2007): UEA CRU Hulme Global precipitation anomalies [mm/month] over the period 1930-1995. **sdv_1** leading pattern of annual-mean variability 1 (fig. 1, first column): "This pattern is statistically related to global SSTs, with the sign such that drying over Africa is associated with warmer tropical Pacific, Indian and South Atlantic Oceans, and a cooler North Atlantic basin". **sdv_2** corresponds to the pattern 2 (fig. 1, second column): "canonical ENSO influence, one that combines the effects of remote, or tropical Pacific, and local, especially Indian Ocean, surface temperatures". **sdv_3** corresponds to the pattern 3 (fig. 1, third column): "pure atmospheric influence of ENSO, the entire tropical troposphere warms during warm ENSO as a response to the warming of central and eastern equatorial Pacific". Malawi villages: *chit* Chitedze: *kas* Kasungu; *lil* Lilongwe; *nkh* Nkhotakota. Tanzania villages: *bab* Babati; *mbu* Mbulu. Kenya villages: *kit* Kitale; *eld* Eldoret; *nak* Nakuru.

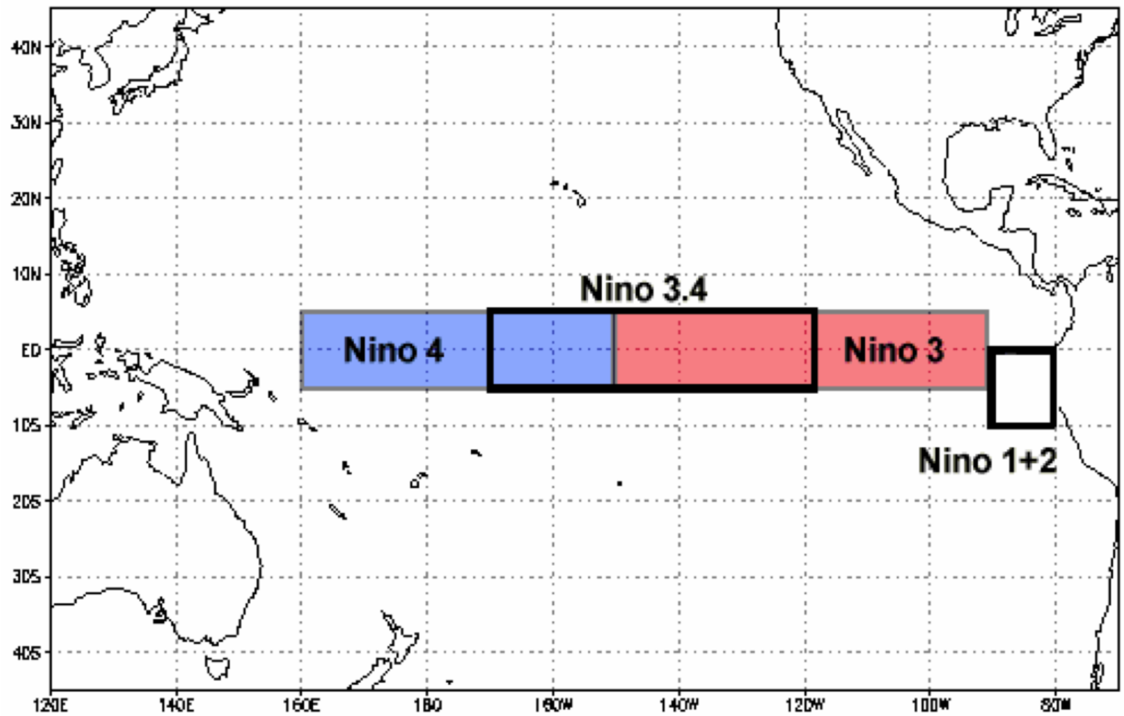


Figure 4.10: Graphical depiction of the four Nino regions (source: NOAA). Definition of the ENSO index NINO 3.4: The index is defined as a three-month running average of sea surface temperature (SST) departures from normal for a critical region of the equatorial Pacific. The Niño 3.4 region is delimited by the following latitude and longitudes: 120W-170W, 5N-5S. El NiÑo or La NiÑa event is then identified if the 3-month running-average of the NINO 3.4 Index exceeds +0.5 deg. C (for El NiÑo; -0.5 deg. C for La NiÑa) during the period October-December.

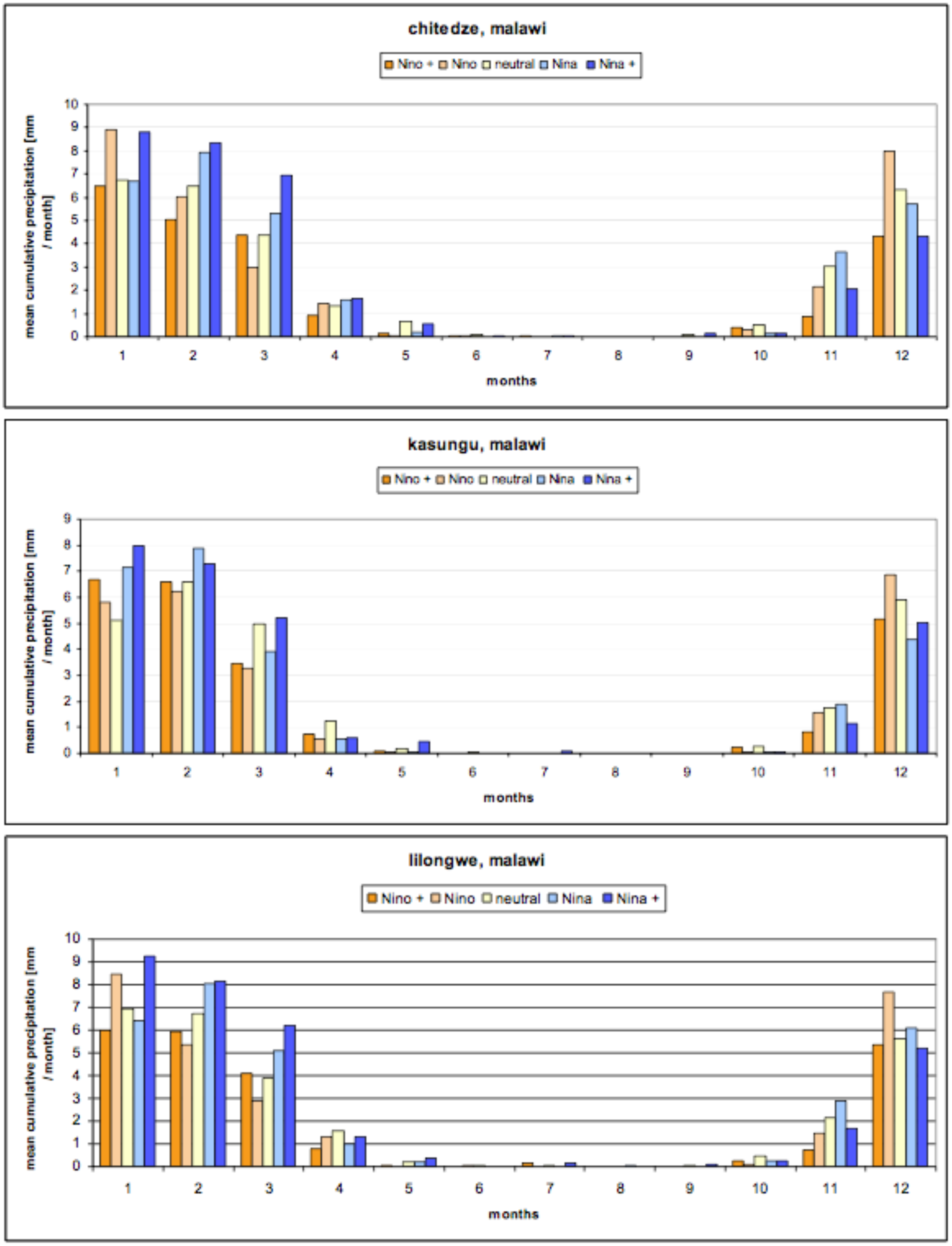


Figure 4.11: In the following graphs: Niño+ (Niña+) indicates a strong El Niño (La Niña) state with index $NINO3.4 \geq 1$ deg C (≤ -1 deg C). Niño (Niña) indicates El Niño (La Niña) state with $NINO3.4 \geq 0.5$ deg C (≤ -0.5 deg C).

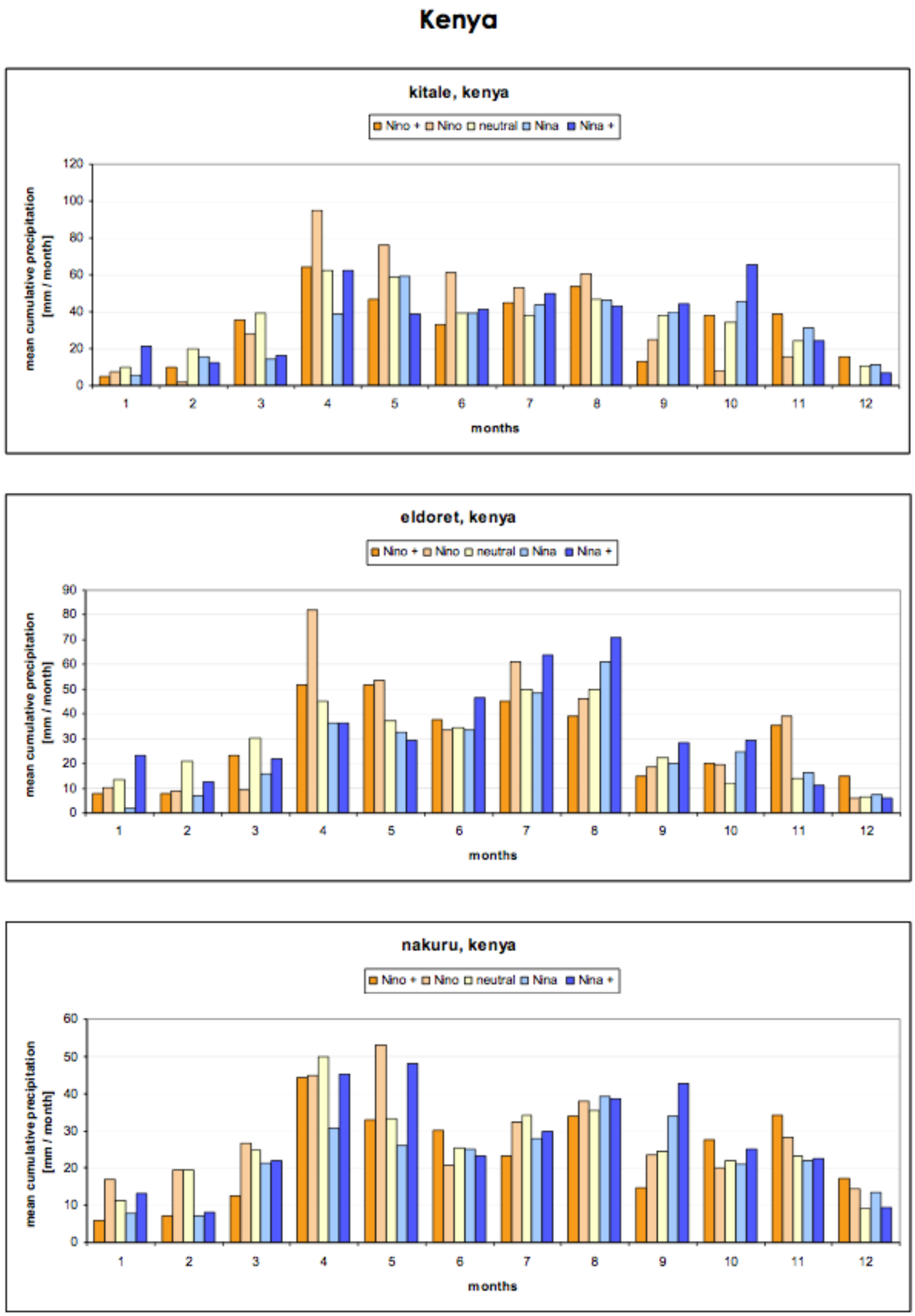
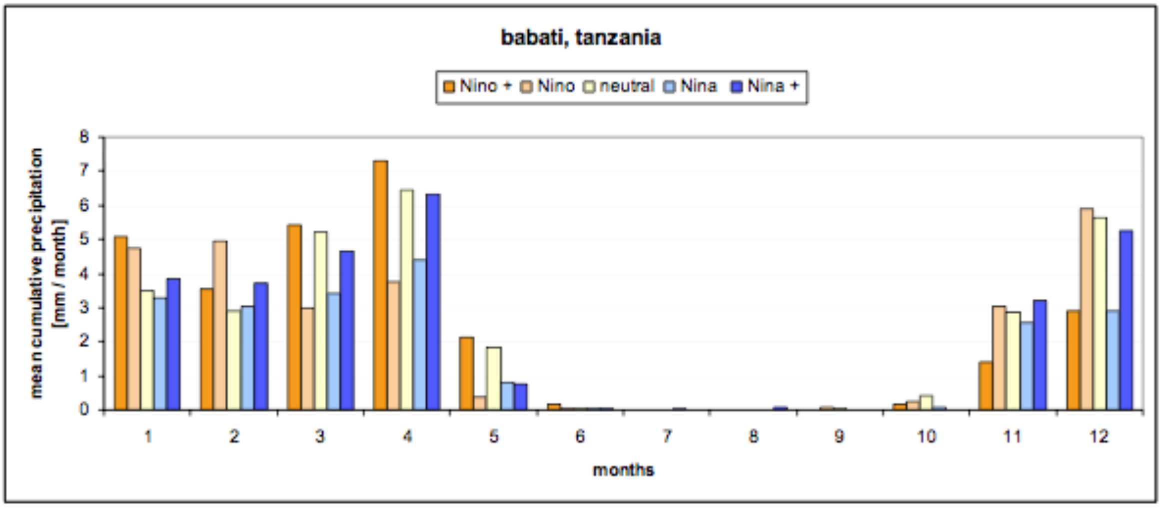


Figure 4.12: Histograms Kenya

Tanzania



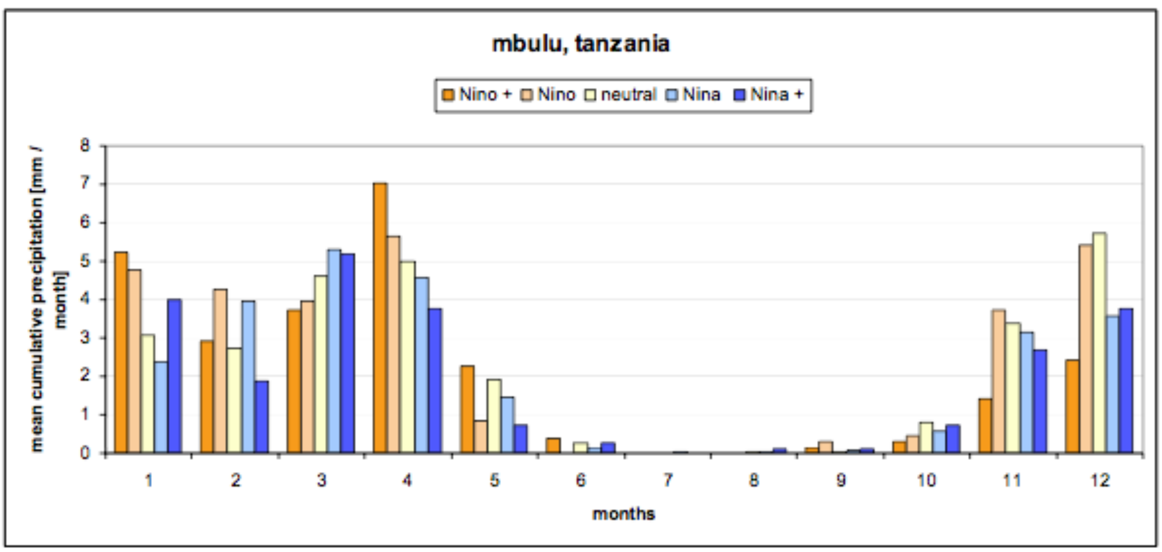


Figure 4.13: Histograms Tanzania

FIGURES 4.14, 4.15, 4.16 PRESENT SIMULATION AND ANALYSIS OF HISTORICAL PAYOUTS. For each village we provide two tables (e.g. upper and lower table) and a chart showing the occurrence of payouts between 1962 and 2005.

1. In the upper table:

Mean Pay is the average payouts that is the sum of payouts divided by the number of years.

VaR is the value at risk; it corresponds to the payout associated to the 99th percentile.

Insurance price (Premium) is calculated using this formula:

= Average(payout) + Loading * (Value at Risk -Average(Payout))

We apply here the pricing utilized in the design work of the 2006 insurance. We calculate here two insurance prices once with loading equal to 6% and 6.5%.

Maximum liability is the limit of coverage provided by an insurance policy (maximum liability is fixed in this table).

Insurance rate is the ratio between insurance price and maximum liability.

Insurance rate = Insurance price / maximum liability

Number of payments indicates the total number of payouts for each ENSO state and for "all" states.

Number of years is the number of years corresponding to the ENSO state indicated as title of each column.

Pay frequency is number of years divided by the total number of years studied (that is number of years in column"all").

2. In the lower table:

The maximum liability is allowed to change, while the insurance price is fixed. The insurance rate is the value calculated above (highlighted in green). Max Liability = Insurance price / Insurance rate

Loan is the loan received by the farmers after they sign the contract that bundle microcredit with microinsurance:

$Loan = Max\_Liability/(1+r) r = 0.275$

Interest corresponds to the loan times the coefficient r: $Interest = Loan \times r$

Input budget is the budget available for inputs (high-yield maize seed and fertilizer):

Input budget = $MaxLiability - Interest - Premium$

Input budget weight is the ratio of IB in different ENSO phases to the IB of the non-ENSO-adjusted package.

Input budget weight = Input budget / (Input budget for All)

3. In order to select years by **ENSO state** we used the index **NINO3.4** corresponding to the period October - December of the year previous to the harvest for Malawi and Tanzania; and the year of the harvest for Kenya.

4. In the payout graphs, different colors correspond to different ENSO states: Green - Neutral years; Blue - El Nino years; Pink - La Nina years.

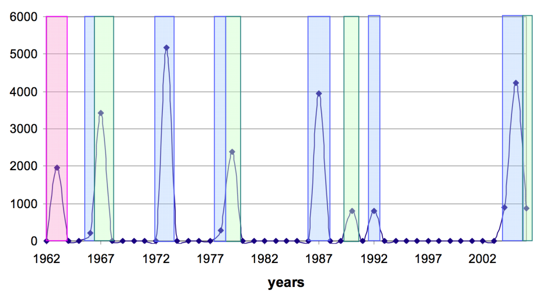
Lilongwe:

	El Nino	La Nina	Neutral	All
Mean Pay	971.44	130.20	536.14	555.60
VaR, payout 99th percentile	5040.9	1679.58	3294.45	4764.24
Insurance Price (loading 6.5%)	1235.95	230.91	715.43	829.16
Insurance Price (loading 6.0%)	1215.61	223.16	701.64	808.12
Insurance Rate	0.1351	0.0248	0.0780	0.0898
Number of Payments	7	1	4	12
Number of Years	16	15	14	45
Pay Frequency	0.44	0.07	0.29	0.27

max liability 9000 9000 9000 9000

	El Nino	La Nina	Neutral	All
Insurance Price fixed	702.90	702.90	702.90	702.90
Insurance Rate	0.1351	0.0248	0.0780	0.0898
Max Liability	5204.07	28347.47	9016.15	7828.18
Loan	4081.63	22233.31	7071.49	6139.75
Interest	1122.45	6114.16	1944.66	1688.43
Input budget	3378.73	21530.41	6368.59	5436.85
Input budget weight	0.62	3.96	1.17	1.00

Lilongwe - payouts



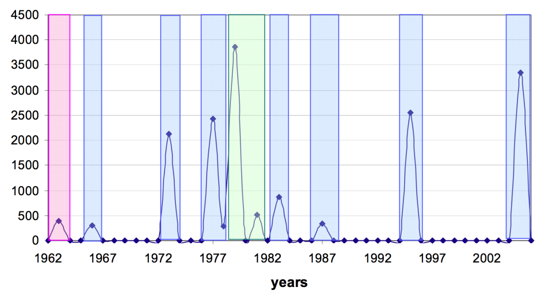
Chitedze:

	El Nino	La Nina	Neutral	All
Mean Pay	764.67	25.89	312.63	377.78
VaR, payout 99th percentile	3224.842	334.0412	3422.265	3630.689
Insurance Price (loading 6.5%)	924.58	45.92	514.76	589.22
Insurance Price (loading 6.0%)	912.28	44.38	499.21	572.95
Insurance Rate	0.1014	0.0049	0.0555	0.0637
Number of Payments	8	1	2	11
Number of Years	16	15	14	45
Pay Frequency	0.50	0.07	0.14	0.24

max liability 9000 9000 9000 9000

	El Nino	La Nina	Neutral	All
Insurance Price fixed	702.90	702.90	702.90	702.90
Insurance Rate	0.1014	0.0049	0.0555	0.0637
Max Liability	6934.37	142532.83	12672.25	11041.23
Loan	5438.72	111790.46	9939.02	8659.79
Interest	1495.65	30742.38	2733.23	2381.44
Input budget	4735.82	111087.56	9236.12	7956.89
Input budget weight	0.60	13.96	1.16	1.00

Chitedze - payouts



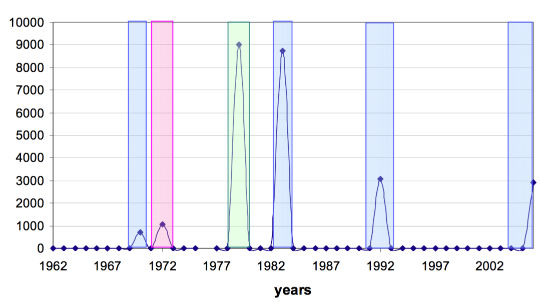
Kasungu:

	El Nino	La Nina	Neutral	All
Mean Pay	781.88	72.00	851.14	566.80
VaR, payout 99th percentile	7882.2	939.6	8209.08	8883.9
Insurance Price (loading 6.5%)	1243.40	128.39	1329.41	1107.41
Insurance Price (loading 6.0%)	1207.89	124.06	1292.62	1065.83
Insurance Rate	0.1342	0.0138	0.1436	0.1184
Number of Payments	3	1	2	6
Number of Years	16	15	14	45
Pay Frequency	0.19	0.07	0.14	0.13

max liability 9000 9000 9000 9000

	El Nino	La Nina	Neutral	All
Insurance Price fixed	702.90	702.90	702.90	702.90
Insurance Rate	0.1342	0.0138	0.1436	0.1184
Max Liability	5237.30	50993.91	4894.02	5935.40
Loan	4107.68	39995.22	3838.44	4655.21
Interest	1129.61	10998.69	1055.57	1280.18
Input budget	3404.78	39292.32	3135.54	3952.31
Input budget weight	0.86	9.94	0.79	1.00

Kasungu - payouts



Nkhotakota

	El Nino	La Nina	Neutral	All
Mean Pay	646.70	574.91	626.35	616.44
VaR, payout 99th percentile	7342.568	4303.1455	6103.289	7657.527
Insurance Price (loading 6.5%)	1081.94	817.24	982.35	1074.11
Insurance Price (loading 6.0%)	1048.46	798.60	954.96	1038.90
Insurance Rate	0.1165	0.0887	0.1061	0.1154
Number of Payments	3	4	3	10
Number of Years	16	15	14	45
Pay Frequency	0.19	0.27	0.21	0.22

max liability 9000 9000 9000 9000

	El Nino	La Nina	Neutral	All
Insurance Price fixed	702.90	702.90	702.90	702.90
Insurance Rate	0.1165	0.0887	0.1061	0.1154
Max Liability	6033.73	7921.46	6624.44	6089.20
Loan	4732.34	6212.91	5195.64	4775.84
Interest	1301.39	1708.55	1428.80	1313.36
Input budget	4029.44	5510.01	4492.74	4072.94
Input budget weight	0.99	1.35	1.10	1.00

Nkhotakota - payouts

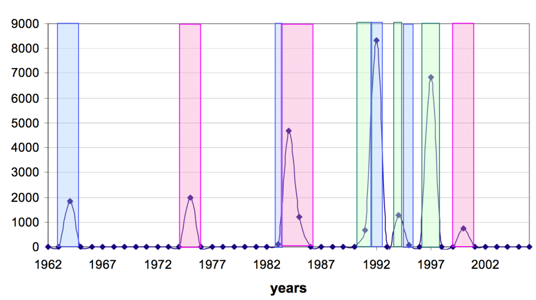


Figure 4.14: Payouts using historical precipitations in Malawi villages.

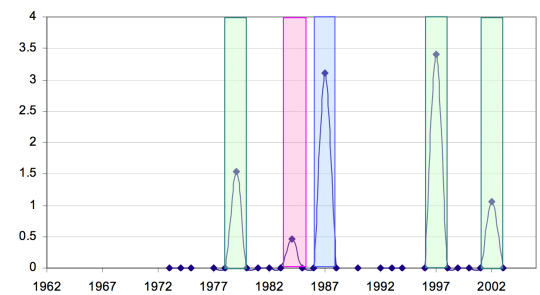
Eldoret:

	El Nino	La Nina	Neutral	All
Mean Pay	0.31	0.05	0.55	0.31
VaR, payout 99th percentile	2.852	0.43431	3.23296	3.322
Insurance Price (loading 6.5%)	0.48	0.07	0.72	0.50
Insurance Price (loading 6.0%)	0.46	0.07	0.71	0.49
Insurance Rate	0.0463	0.0070	0.0707	0.0490
Number of Payments	1	1	3	5
Number of Years	10	10	11	31
Pay Frequency	0.10	0.10	0.27	0.16

max liability 10

	El Nino	La Nina	Neutral	All
Insurance Price fixed	0.50	0.50	0.50	0.50
Insurance Rate	0.0463	0.0070	0.0707	0.0490
Max Liability	10.81	71.47	7.07	10.21
Loan	8.48	56.06	5.55	8.01
Interest	2.33	15.42	1.53	2.20
Input budget	7.98	55.56	5.05	7.51
Input budget weight	1.06	7.40	0.67	1.00

Eldoret - payouts



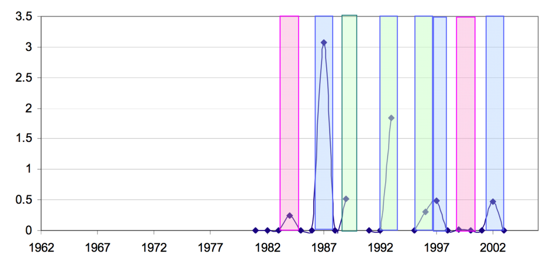
Kitale

	El Nino	La Nina	Neutral	All
Mean Pay	0.44	0.16	0.31	0.30
VaR, payout 99th percentile	2.8858	0.50722	1.761922	2.82466
Insurance Price (loading 6.5%)	0.60	0.18	0.41	0.47
Insurance Price (loading 6.0%)	0.59	0.18	0.40	0.45
Insurance Rate	0.0585	0.0177	0.0399	0.0454
Number of Payments	1	4	3	8
Number of Years	7	7	9	23
Pay Frequency	0.14	0.57	0.33	0.35

max liability 10

	El Nino	La Nina	Neutral	All
Insurance Price fixed	0.50	0.50	0.50	0.50
Insurance Rate	0.0585	0.0177	0.0399	0.0454
Max Liability	8.54	28.19	12.55	11.01
Loan	6.70	22.11	9.84	8.63
Interest	1.84	6.08	2.71	2.37
Input budget	6.20	21.61	9.34	8.13
Input budget weight	0.76	2.66	1.15	1.00

Kitale - payouts



Nakuru

	El Nino	La Nina	Neutral	All
Mean Pay	0.38	0.38	0.05	0.27
VaR, payout 99th percentile	2.7437	1.49066	0.6003	2.4866
Insurance Price (loading 6.5%)	0.54	0.45	0.09	0.41
Insurance Price (loading 6.0%)	0.52	0.45	0.08	0.40
Insurance Rate	0.0523	0.0447	0.0084	0.0401
Number of Payments	2	4	1	7
Number of Years	13	12	13	38
Pay Frequency	0.15	0.33	0.08	0.18

max liability 10

	El Nino	La Nina	Neutral	All
Insurance Price fixed	0.50	0.50	0.50	0.50
Insurance Rate	0.0523	0.0447	0.0084	0.0401
Max Liability	9.56	11.19	59.35	12.46
Loan	7.49	8.78	46.55	9.78
Interest	2.06	2.41	12.80	2.69
Input budget	6.99	8.28	46.05	9.28
Input budget weight	0.75	0.89	4.96	1.00

Nakuru - payouts

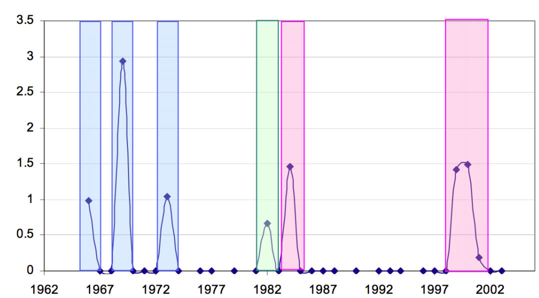


Figure 4.15: Payouts using historical precipitations in Kenya villages.

Babati

	El Nino	La Nina	Neutral	All
Mean Pay	34.63	51.70	64.31	50.06
VaR, payout 99th percentile	350.428	363.213	286.8189	383.63
Insurance Price (loading 6.5%)	55.15	71.95	78.77	71.75
Insurance Price (loading 6.0%)	53.58	70.39	77.66	70.08
Insurance Rate	0.0536	0.0704	0.0777	0.0701
Number of Payments	1	2	4	7
Number of Years	11	8	11	30
Pay Frequency	0.09	0.25	0.36	0.23

max liability 1000 1000 1000 1000

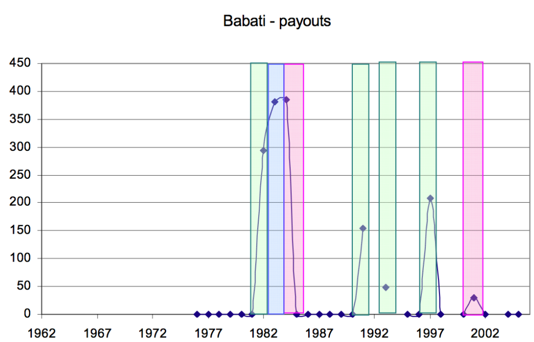
	El Nino	La Nina	Neutral	All
Insurance Price fixed	50.00	50.00	50.00	50.00
Insurance Rate	0.0536	0.0704	0.0777	0.0701
Max Liability	933.27	710.28	643.85	713.49
Loan	731.97	557.09	504.98	559.60
Interest	201.29	153.20	138.87	153.89
Input budget	681.97	507.09	454.98	509.60
Input budget weight	1.34	1.00	0.89	1.00

Mbulu

	El Nino	La Nina	Neutral	All
Mean Pay	51.99	80.55	82.50	70.79
VaR, payout 99th percentile	342.375	600.2125	481.9	604.975
Insurance Price (loading 6.5%)	70.86	114.33	108.46	105.51
Insurance Price (loading 6.0%)	69.41	111.73	106.46	102.84
Insurance Rate	0.0694	0.1117	0.1065	0.1028
Number of Payments	2	2	3	7
Number of Years	11	8	11	30
Pay Frequency	0.18	0.25	0.27	0.23

max liability 1000 1000 1000 1000

	El Nino	La Nina	Neutral	All
Insurance Price fixed	50.00	50.00	50.00	50.00
Insurance Rate	0.0694	0.1117	0.1065	0.1028
Max Liability	720.34	447.52	469.64	486.18
Loan	564.97	351.00	368.35	381.32
Interest	155.37	96.52	101.30	104.86
Input budget	514.97	301.00	318.35	331.32
Input budget weight	1.55	0.91	0.96	1.00



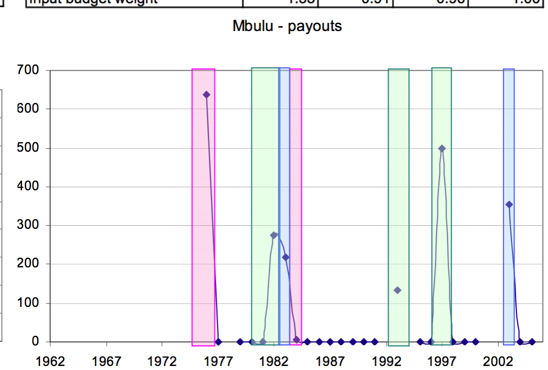
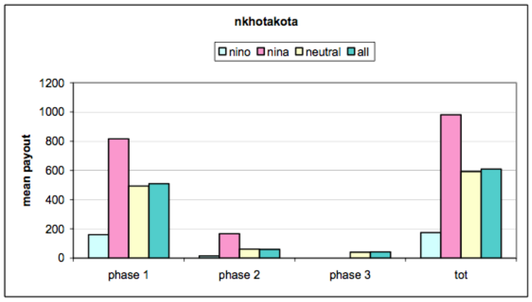


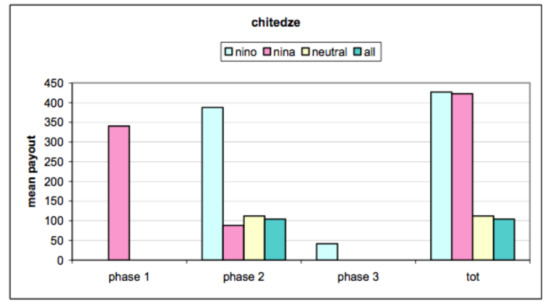
Figure 4.16: Payouts using historical precipitations in Tanzania villages.

mean:

	nkhotakota			
	phase 1	phase 2	phase 3	tot
nino	160.4804	13.86317	0.364137	174.7077
nina	817.147	167.0962	0	980.4292
neutral	492.8781	61.80338	40.29681	593.1708
all	510.3098	59.92667	42.69529	610.0428

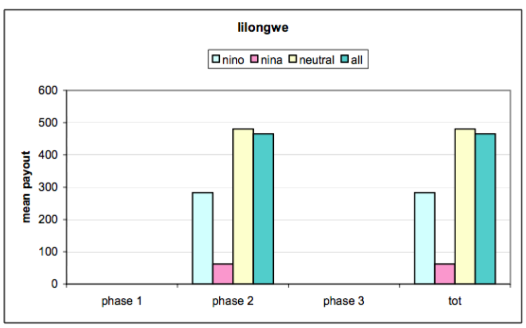
	chitedze			
	phase 1	phase 2	phase 3	tot
nino	0	388.0041	41.9349	426.9248
nina	340.9338	88.38886	0	422.5626
neutral	0	112.2033	0	112.2033
all	0	104.1812	0	104.1812

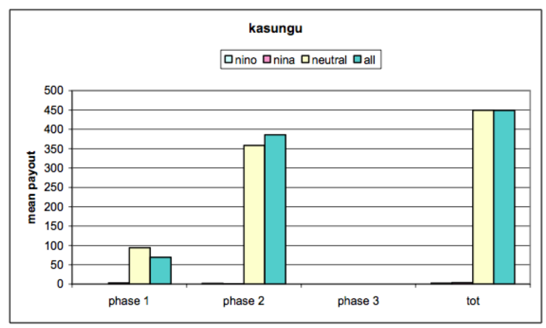




	lilongwe			
	phase 1	phase 2	phase 3	tot
nino	0	283.0901	0	283.0901
nina	0	62.42442	0	62.42442
neutral	0	480.0628	0	480.0628
all	0	465.433	0	465.433

	kasungu			
	phase 1	phase 2	phase 3	tot
nino	0.203412	2.404455	0	2.607867
nina	3.165461	0.940814	0	4.106275
neutral	94.25616	358.4128	0	449.5839
all	69.74136	386.0438	0	449.1215





variance:

	nkhotakota			
	phase 1	phase 2	phase 3	tot
nino	132612.83	5240.32	132.5958	138466.2
nina	1006428.8	127913.1	0	1127414
neutral	625034.32	35676.77	102134.4	743074.2
all	633738.48	32459.59	109769.6	754018

	chitedze			
	phase 1	phase 2	phase 3	tot
nino	0	473077.9	144398.1	584510.8
nina	1120975	70187.62	0	1139501
neutral	0	93660.53	0	93660.53
all	0	78856.09	0	78856.09

	lilongwe			
	phase 1	phase 2	phase 3	tot
nino	0	329249.2	0	329249.2
nina	0	47441.63	0	47441.63
neutral	0	612760.5	0	612760.5
all	0	569872.8	0	569872.8

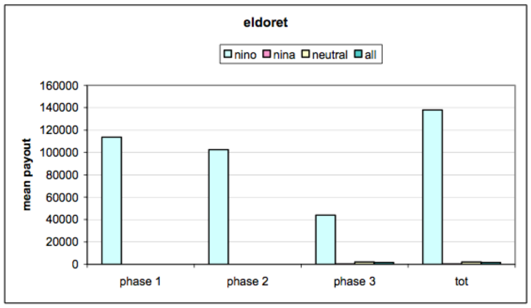
	kasungu			
	phase 1	phase 2	phase 3	tot
nino	41.37639	2265.564	0	2305.961
nina	5631.503	490.0966	0	6115.638
neutral	243337.7	692871.6	0	888156.2
all	181339.6	739922.2	0	865295.3

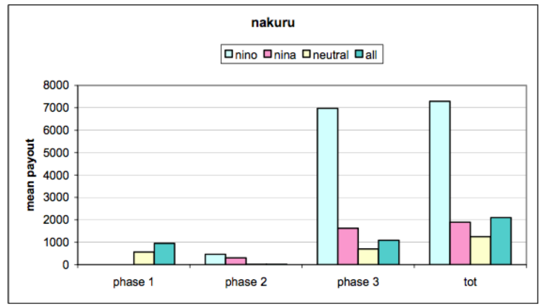
Figure 4.17: Results of Monte Carlo Simulations for Malawi.

mean:

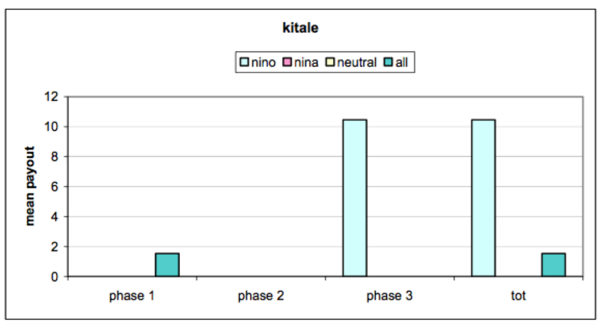
	eldoret			
	phase 1	phase 2	phase 3	tot
nino	113709.2	102561.7	43907.41	138087.9
nina	16.62496	0	277.4343	292.6204
neutral	0	0	2000.47	2000.47
all	0	0	1593.153	1593.153

	nakuru			
	phase 1	phase 2	phase 3	tot
nino	0	466.3454	6978.955	7289.76
nina	0	304.8963	1627.026	1896.638
neutral	568.8413	14.09386	696.5178	1245.687
all	951.5207	16.94261	1090.248	2104.495





	kitale			
	phase 1	phase 2	phase 3	tot
nino	0	0	10.45664	10.45664
nina	0	0	0	0
neutral	0	0	0	0
all	1.535298	0	0	1.535298



variance:

	eldoret			
	phase 1	phase 2	phase 3	tot
nino	132612.8	5240.32	132.5958	138466.2
nina	1006429	127913.1	0	1127414
neutral	625034.3	35676.77	102134.4	743074.2
all	633738.5	32459.59	109769.6	754018

	nakuru			
	phase 1	phase 2	phase 3	tot
nino	0	473077.9	144398.1	584510.8
nina	1120975	70187.62	0	1139501
neutral	0	93660.53	0	93660.53
all	0	78856.09	0	78856.09

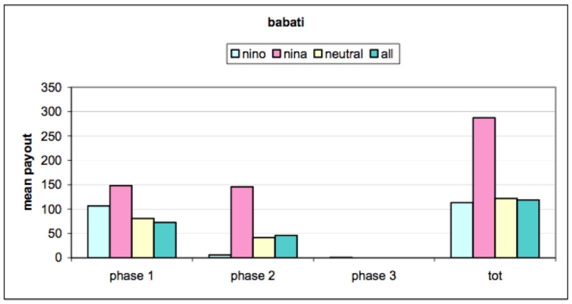
	kitale			
	phase 1	phase 2	phase 3	tot
nino	0	329249.2	0	329249.2
nina	0	47441.63	0	47441.63
neutral	0	612760.5	0	612760.5
all	0	569872.8	0	569872.8

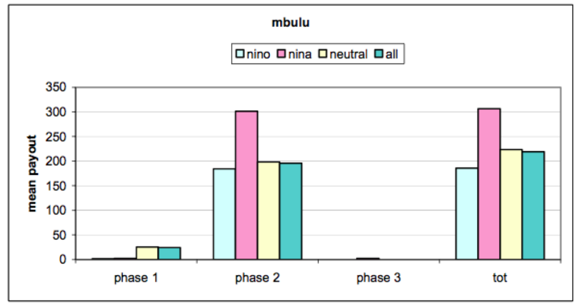
Figure 4.18: Results of Monte Carlo Simulations for Kenya.

mean:

	babati			
	phase 1	phase 2	phase 3	tot
nino	106.5606	5.824172	1.024971	113.4097
nina	148.2374	145.691	0.067363	287.4043
neutral	80.78396	41.39025	0	121.6886
all	72.59758	46.27296	0.019143	118.757

	mbulu			
	phase 1	phase 2	phase 3	tot
nino	1.480476	184.4637	0	185.9441
nina	2.859236	301.1171	2.609158	306.569
neutral	25.618	198.4569	0	223.8066
all	24.41036	195.8647	0	219.2262





variance:

	babati			
	phase 1	phase 2	phase 3	tot
nino	36449.67	952.1567	27.32956	38221.06
nina	63529.22	49980.03	2.054432	99772.47
neutral	23535.72	12521.57	0	36097.36
all	19892.6	15199.76	0.366444	35382.78

	mbulu			
	phase 1	phase 2	phase 3	tot
nino	290.3899	41924.11	0	42136.06
nina	747.5332	76044.69	77.16514	76382.53
neutral	10792.87	44105.76	0	54187.19
all	10187.5	43971.95	0	53330.63

Figure 4.19: Results of Monte Carlo Simulations for Tanzania.

Chapter 5

Perspectives

5.1 Linking Indigenous and Scientific Knowledge of Climate Change

The paper "Attributing Physical and Biological Impacts to Anthropogenic Climate Change", presented in chapter 2, attributed for the first time physical and biological changes across the globe to anthropogenic climate change. Our work contributed also to the 2007 IPCC 4th Assessment Report (Working Group II). The underlying meta-analyses and aggregation of data included only scientific studies selected under very strict criteria: peer-reviewed papers, demonstrating significant trend in change in either direction related to temperature and containing data for at least 20 years between 1970 and 2004. The Observed Climate Change Impacts Database that we constructed for this study contains a sheer number of observations: 80,000 data-series from 577 peer-reviewed studies. However, we found a significant lack of geographical balance in the data and literature on observed changes in natural and managed systems, with a marked scarcity in the sub-polar regions, in the tropics and in developing countries in general. In these regions indigenous knowledge could complement scientific monitoring in assessing the effects of a changing climate.

Climate change's negative effects on indigenous communities include: disruption of the food supply associated to temperature-driven migration of indigenous species (Mustonen (2005), IPCC (2007), Diffenbaugh et al. (2007)); increased susceptibility to diseases whose epidemiology is affected by environmental factors such as precipitation and temperature (IPCC (2001), US Global Change Research Program (2001), Green et al. (2009)); and cultural disturbances and losses (Sakakibara (2008) and (2009)). Climate change is felt disproportionately by indigenous communities, particularly in the polar and sub-polar regions; and indigenous narratives provide long time series of ecological and physical phenomena (e.g timing of migration of animals, changes in indigenous species in a region, timing of seasonal ice melting in the polar region). Indigenous narratives have never been included in scientific assessments but they might represent an important source of information, particularly in areas with marked data scarcity. Moreover, in remote areas that do not have temperature records, indigenous knowledge narratives can serve as proxy data.

In 2008, I took part to a panel brought together by the Center for Biodiversity and Conservation of the American Museum of Natural History (AMNH) as part of a larger conference titled *Sustaining Cultural and Biological Diversity in a Rapidly Changing World*. The goal of the panel, composed by scientist and indigenous people leaders, was to explore the challenges posed by climate change to indigenous groups.

After the event, members of the panel kept working together to explore possible ways to integrate indigenous knowledge and science. As part of this project, with financial support from the AMNH, we developed a database of indigenous narratives brought forward by the conference participants, and studied the spatial correlation of these observations with documented temperature changes and peer-reviewed studies from the Observed Climate Change Impacts Database. A discussion of these exploratory analyses is presented in a study I co-authored with the other 12 members of the panel, and just accepted for publication in *BioScience* (Alexander et al. (2011)). We find that peer-reviewed observations and indigenous knowledge narratives located in close proximity (less than 50km apart) are complementary in that both are reporting system changes consistent with warming temperatures. The narratives contained in our still embryonic database show that global climate change is already affecting integrated physical, biological, and human eco-systems, especially in the northern high latitudes. As part of our study we also propose a framework to foster linkages between indigenous narratives of observed climate change with global scientific assessments. Such a process of inclusion would enhance the IPCC Fifth Assessment (AR5) process, now underway.

5.2 Socio-economic Impacts of Weather Shocks

Chapter 3 studies the vulnerability of rural households to two types of weather shocks (i.e. droughts and extreme rainfall events), using consumption as a metric, and investigates post-shock decisions to migrate of family members. Two new research projects have developed from this study and are currently underway. My coauthor[1] and I will use the dataset that I constructed by joining weather data and the Progresa longitudinal socio-economic dataset to explore longer-term impacts of ENSO-related weather extremes (occurred in 1997, 1998 and 1999) on two different dimensions of socio-economic development: child health and long-term migration. In both studies my coauthor and I plan to use additional data collected in follow up surveys of the Progresa datasets in 2003 and 2007.

[1] Arturo Aguilar, doctoral student in the Economics Department of Harvard University.

5.2.1 Long-term impacts of weather extremes on child health

El Niño Southern Oscillation (ENSO) has a cycle of 5-7 years, and it affects precipitation and consequently agricultural yields in numerous developing countries (Cane et al., 1994) from Latin America to Africa. However, little is known about the impact of cyclical climatic events on long-term human capital accumulation. In rural areas, dominated by rainfed subsistence farming, food-consumption can be strongly affected by weather conditions. Malnutrition induced by a drought or an excess rain event represents a major risk during the early stages of child development. Developmental biology teaches that stressful conditions – such as malnutrition – in utero and/or during the first years of life can have irreversible long-term negative consequences on child health and cognitive development. In this project we will study the long-term influence of ENSO-related weather extremes on human capital accumulation, namely health, cognitive and educational attainments. Our household data allows us to examine the impact of weather shocks occurred at two different stages of child development, in utero, and in the first years of life after birth[2]. Also, we will analyze to what extent cash transfers from the Progresa poverty alleviation program aid households to reduce their vulnerability to this kind of shocks.

For our research, we rely on and will contribute to two main strands of literature: the growing body of literature studying the long-term impacts of exogenous shocks (in particular, weather shocks) on child development and human capital accumulation; and the vast literature on poverty-alleviation programs' direct and indirect impacts.

The idea that stimuli or stressful conditions during critical or sensitive periods in early life can have lifetime consequences is well established in developmental biology and is known as *fetal programming* (Barker, 1998). Moreover, from a purely nutri-

[2]Weather shocks were not uniformly distributed in the region under exam, thus our control group includes children in villages unaffected by shocks.

tional point of view, the *fetal origins hypothesis* states that individuals born small because of malnutrition are predisposed to adult diseases and reduced body size. Several economic studies have documented the long term impacts of *in-utero* shocks (e.g. Behrman and Rosenzweig (2004), Almond (2006) and Almond et al. (2010)).

Other studies suggest that shocks occurred in the *first years* after birth have significant negative impacts on child development too. Hoddinot and Kinsey (2001) and Alderman, Hoddinott, and Kinsey (2006) use data from Zimbabwe to show that drought-induced malnutrition for children between one and two years of age is causally related to reduced human capital formation. Similarly, Maccini and Yang (2009), using Indonesian data for females, find that local rainfall variations around the time of birth significantly affect schooling, health and socio-economic status in adulthood.

Our project builds on the study presented in Chapter 3 of this dissertation. Using the Progresa-survey dataset, I found strong contractions in food and non-food consumption after extreme weather events occurred in 1998-1999. Weather-induced contractions in food-consumption at the household level might have in turn caused in utero and/or post-birth nutritional deprivation, with long term consequences on health and educational achievements. In the first part of our study we will test this hypothesis.

We will use a larger spectrum of health and cognitive development indicators: birth-weight, anthropometric measures for older children (i.e. body mass index, height and weight), level of hemoglobin in the blood, Peabody Test (a measure of verbal ability), Woodcock Johnston Test[3], McCarthy coordination test. We will use the number of completed grades of schooling in 2007 as a measure for educational attainment. Anthropometric measures and hemoglobin are objective measures collected during visits at local clinics, used as standard indicators for *stunting* (defined

[3]The Woodcock Johnston Test measures: visual-spatial thinking, auditory processing, fluid reasoning, short-memory.

as being two or more standard deviations below the age-sex standardized height of a healthy (U.S.) reference population (World Health Organization, (1979)) and *anemia* (defined as hemoglobin less than 11 g/dL adjusted for altitude). The Peabody, Woodcock Johnston and McCarthy tests (performed when the child is 2 to 6-year old) are used as predictors of cognitive development and future academic achievements.

In the second part of our study, we will examine the role of CCT/Progresa in mitigating the negative impacts of weather shocks. By design, the CCT/Progresa was aimed at improving the educational, health and nutritional status of children living in extreme poverty[4]. Because of its robust impact evaluation design, CCT/Progresa's direct and indirect impacts have been widely investigated. All primary indicators of direct impacts (e.g. school enrollment, preventive health check-ups for growth monitoring and vaccinations, pre-natal care, food availability and nutritional status) on beneficiary households compared with control households have shown significant increases in the expected direction (Skoufias, (2001)). CCT/Progresa seems to have produced also several indirect significant impacts in beneficiary households (e.g. improvements in women's status and increase in monthly consumption per person) (Adato et al., (2000); Hoddinott et al., (2000)) and positive spillover effects on non-beneficiary households (Handa et al., (2001); Angelucci et al. (2010)). The study by Gertler (2004) is particularly informative for our analysis: by using high, weight and hemoglobin levels as dependent variables, he found positive health outcomes associated with Progresa for children of beneficiary households in 1998-2000. Our analysis will expand Gertler's study in several ways: first, we will not focus only on Progresa

[4]The cash transfer was addressed to mothers and conditional on participating in four sets of activities to promote family health and nutrition: (i) Nutritional supplements for children age 0-2 and for pregnant and lactating women; (ii) Growth monitoring from conception till 5 years of age; (iii) Preventive medical care including prenatal care, baby care and immunizations, and adult preventive visits to clinics; and (iv) Education programs on health, hygiene, and nutrition habits.

but on the interaction between Progresa and weather shocks; second, our study will cover a longer time period considering also long-term health effects measured in 2003 and 2007; and third, we will consider both health and cognitive development outcomes.

5.2.2 Climate-driven migration

The second research project will focus on the relationship between weather shocks, such as persistent droughts and extreme rainfall, and the decision to migrate of members of Mexican rural households. In particular, the role of the extreme El Niño events will be considered. Our study aims at deepening our understanding of the motives to migrate when faced with climate-related shocks.

Seasonal, temporary or permanent migration can be an important risk management strategy for rural households affected by weather shocks. However, little is known about the impact of weather extremes on both temporary and permanent migration from developing countries.

A puzzle emerged in the development economics literature is that the poor do not migrate for long periods. Seasonal or temporary migration of a family member seems to be common among rural households in the developing world, while permanent migration is rare (Banerjee and Duflo, 2007). A possible explanation is related to social networks. Munshi and Rosenzweig (2009) argue that the lack of long-term migration reflects the value of remaining close to one's social network, in a setting where the social network might be the only source of (informal) insurance available to people. Short-term migrants are able to maintain their social links through their family that remains in the village of origin.

Our research project will investigate the dynamic behind permanent and temporary migration of family members by exploiting the diverse weather patterns in the region under exam. We will study the profiles of migrants who respond to weather shocks and migrants under "normal" conditions. Our dataset allows us to also explore differences between domestic and international migration, and the role of gender in migration decisions.

The Progresa database tracks each family member for 10 years. We will use 6 rounds of the dataset, 4 surveys between 1997 and 2000, and the 2 follow-up surveys in 2003 and 2007. Every round of the Progresa survey includes a migration section asking if any member of the household lives elsewhere, where (i.e. different locality, different municipality, different state, or abroad), when the person leaved (i.e. month and year), and for what reason (i.e. to attend school, for professional reasons, because of economic problems, or because the person got married). Data about frequency and amount of remittances are also included. Furthermore, the dataset allows us to explore additional factors that might be related to migration decisions: gender, age, level of education, parents' level of education, size of the household, household assets, land-use practices at the household level, existing networks of migrants within the same household, family or village.

This project will investigate several aspects of migration, and we expect to present my results in a series of papers. First, we will explore seasonal, temporary (if the household member is away for less than 10 years), and permanent migratory patterns. we will study drivers and socio-economic characteristics associated to short-term versus long-term migration. we will also explore drivers and characteristics of short-distance versus long-distance migration (e.g. domestic versus international migration).

Second, we will study the role of gender: in low-income households it is usually adult males who migrate and leave their family behind, we will test this hypothesis comparing female migration from households affected by different weather shocks or no shocks (i.e. my control group).

Third, we shall investigate the effect of the interaction between the government intervention CCT/Progresa and weather shocks on migration decisions. CCT/Progresa is designed to target children in poor households by providing cash payments to mothers in exchange for regular school attendance, health clinic visits, and nutritional support. The impact of the conditional cash transfer on migration is uncertain: on one side, the government intervention might help smooth consumption and reduce migration of family members (e.g. father, older brothers or sisters); on the other side, the cash transfer might loosen financial constraints and facilitate the decision to migrate of family members. We will test these two hypothesis by comparing migration decisions in beneficiary versus non-beneficiary households in the event of weather shocks. Our control group includes households that did not receive the government intervention and that were not affected by weather shocks. In a recent paper, Angelucci (2010) used the CCT/Progresa dataset to estimate the effect of the government transfers on migration. Her estimates suggest that the program is associated with an increase in international migration (but not domestic migration). Our study would complement Angelucci's analysis by taking into account weather shocks.

5.2.3 Forecasting social cost of adaptation to climate change

Our results from the two projects just described will also have bearing on the analysis of impacts of future climate change. Climatic projections forecast more frequent extreme weather events in several tropical and subtropical regions, coinciding geographically with developing countries. Our results will provide a test bed for studying climate impacts on health and migration of future global climate change; in the final stage of the project, we plan to use our estimated models to predict future impacts under different model-based probabilistic climate change scenarios provided from the NASA-GISS Climate Impacts Group. Keeping in mind factors specific to Mexico, the goal of this projection exercise will be to explore the potential magnitude of future impacts on human capital and migration decisions. From a policy perspective, our work will be informative about the social cost of weather extremes and adaptation to climate change.

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