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Regional Inequality and Polarization in the Context of Concurrent Extreme Weather and Economic Shocks

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SUMMARY

This study examines how extreme weather in the context of on-going economic shocks influence regional inequality and polarization within Mozambique. Utilizing satellite-based estimates of rainfall that we spatially analyze within a GIS, we establish a 16-year rainfall climatology and calculate monthly rainfall anomalies for 674 villages. We approximate storm-total rainfall from all tropical cyclones entering the Mozambique Channel, as well as the extent of damaging winds for those making landfall, between 2005 and 2008. We group villages according to tropical cyclone impacts and use hierarchical cluster analysis to group the remaining villages according to shared patterns of monthly rainfall anomalies. Using economic data from the 2005 and 2008 National Agricultural Survey of Mozambique, we relate weather patterns associated with near normal rainfall, tropical cyclones and flooding, and drought to changes in inequality and polarization by conducting decomposition analyses of the Gini index and Duclos-Esteban-Ray (DER) polarization index. Our findings mainly correspond to the generally accepted view that weather shocks exacerbate existing economic income and divisions within societies. However, in some cases we find evidence that inequality and polarization can decline in the aftermath of an extreme event, and increase even where the weather is relatively good. By identifying varying effects of extreme events on inequality and polarization at sub-national level, our study enables a more detailed understanding of weather-related effects on socio-economic outcomes in rural societies rapidly integrating into the global economy.

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1 INTRODUCTION

A large body of research indicates that inequality hinders poverty reduction, particularly in the least developed countries (LDCs). Evidence suggests that the more unequal a country's income distribution, the less rapidly its poverty rate falls (World Bank, 2006; Cornia, 2004). Income disparities also allow economic power to be translated into intensifying social injustice (Sen, 1981). Many LDCs are rapidly integrating into the global economy via export-based development strategies and liberalizing markets, dramatically altering the conditions under which people construct their livelihoods. LDCs also face increasing exposure to climate variability and higher frequencies of extreme events (IPCC, 2007). Yet, how people adapt to economic globalization and environmental uncertainty depends on their initial position in society, since this shapes their livelihood opportunities and ability to influence change (Narayan et al. 2000; Sen, 1999).

Research has found that poorer inhabitants of LDCs are disproportionally vulnerable to the negative effects of both economic and environmental shocks (Ahmed et al., 2009; Leichenko and O'Brien, 2008; Nissanke and Thorbecke, 2006). They are more likely to engage in livelihoods that depend on climate-sensitive sectors like agriculture or on low-income informal or temporary jobs with little protection against climate-related employment disruptions (Cunguara et al., 2011; Jones et al., 2009). They also tend to have fewer assets or insurance to help them recover from climate shocks and are more likely to live in areas with high exposure to climate variability and extreme events (Carter et al., 2006; Skoufias et al., 2012). A growing consensus exists within the research literature that poverty makes people more vulnerable to extreme weather events, and that these events exacerbate existing inequalities and power disparities within societies (IPCC, 2014a, 2014b). However, with few exceptions (Grineski et al., 2012), empirical work on the effects of such events on inequality remains relatively limited, particularly at the sub-national level (Leichenko and Silva, 2014).

Mozambique provides a particularly useful case for studying the linkages between extreme weather, inequality, and polarization in the context of high poverty and rapid economic change. Seventy percent of the Mozambican population lives in rural areas, which are still largely reliant on rain-fed, semi-subsistence agriculture (INE, 2008). Mozambican farmers experience high weather vulnerability, with substantial inter- and intra-annual rainfall variability ranging from extreme drought to flooding rainfall from tropical cyclone systems (Arndt, et al., 2010; Matyas & Silva, 2013). However, a key component of the government's rural development policy involves encouraging smallholders to increase agricultural production for international markets (GOM, 2006, 2011). The effectiveness of this approach appears questionable given that high levels of economic growth have not decreased rural poverty (Arndt et al., 2012; Cunguara & Hanlon, 2012; Hanlon & Smart, 2008; Geisbert & Schindler, 2012). Mozambique's GDP per capita rose from $313 in 2005 to $435 in 2008 (World Bank, 2014). Yet 57% of rural Mozambicans still lived below the official poverty line as of 2008/9 (DNEAP/MPD, 2010). In 2007. Mozambique ranked 172nd out of 182 countries according to the Human Development Index (UNDP, 2009), further illustrating the low quality of life for most people. In addition, the Mozambican government reports high levels of national-level inequality, as measured by the Gini coefficient which remained virtually unchanged between 2002-3 (0.42) and 2008-9 (0.41) (DNEAP/MPD, 2010).[1]

Using the double exposure framework (Leichenko and O'Brien, 2008), we examine distributional shifts in income and polarization in the context of concurrent shocks associated with economic globalization and increasing weather variability. During the time period of

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[1] Official inequality figures use consumption expenditure data which typically result in lower Gini coefficients than those derived from income data.

this study (2005-2008) Mozambique experienced multiple weather shocks including extreme rainfall and wind damage from two tropical cyclones, major flooding along the Zambezi River, and drought across the southern regions of the country. These adverse agro-climatic conditions contributed to declines in per capita agricultural production (Arndt et al., 20012). Several economic shocks also occurred, most notably dramatic increases in food and fuel prices which peaked in 2008 (Arndt et al., 2012) and contributed to widespread rioting in February of that year (Hanlon, 2009). The Mozambican government has continued to promote market liberalization policies (Silva, 2014), and research in other rapidly globalizing countries has found empirical linkages between increasing trade openness and intensifying economic and social inequities (Li & Wei, 2010; Liao & Wei, 2012).

In this study, we use the case of Mozambique to test two hypotheses regarding the relationship between inequality and differential climate vulnerability in LDCs based on the conclusions of the latest IPCC report (2014a, 2014b). First, we hypothesize that regions in Mozambique affected by extreme weather events will experience increasing inequality and polarization due to varying household capacity to mitigate the impacts of these events. Second, we hypothesis that, ceteris paribus, regions with normal or near-normal rainfall lead to greater income convergence between subsistence farmers and wealthier households that tend to have more formal, non-agricultural sources of income. After examining these hypotheses, we contextualize our findings, with reference to ongoing economic shocks and other factors that may have inequality-altering effects. Thus we investigate changing income distributions, and the dynamics driving these shifts, at the sub-national level to identify how these shifts may be related to extreme weather events in the context of rapid economic change.

2 MATERIALS AND METHODS

Socio-Economic Data and Variable Construction

We use household-level micro-data from the National Agricultural Survey of Mozambique (Trabalho de Inquérito Agrícola TIA) for 2005 and 2008 produced by the Mozambican Ministry of Agriculture (MINAG 2005, 2008). Data were collected each year from a nationally representative sample of households. The surveys provide information (including demographic characteristics, household economic activities and income, and agricultural production) for 6,149 households in 2005 and 5,968 in 2008. Although the TIA data represent the most comprehensive, on-going assessment of socio-economic conditions in Mozambique, the survey does not collect information regarding consumption or asset values. Thus our study is limited to an analysis of income levels.

As households from different villages were surveyed in 2005 and 2008, we subset the TIA samples to include only those located in localidades – Mozambique's smallest administrative unit – that were visited in both years. We plotted the geographic locations of villages on the same grid used for our rainfall analysis (See Section 2.1). When possible, we subdivided localidades where villages were dispersed over multiple grid cells to better ensure that villages were grouped together according to shared rainfall patterns. The resulting data set includes 674 villages, with socio-economic and rainfall data for 3,321 and 2,603 households in 2005 and 2008 respectively.

Following the method outlined by Mather, Cunguara, and Boughton (2008), every sample household's total income for each year is derived by calculating income from agricultural crop and livestock production, agricultural wage labor, non-agricultural wage labor, non-agricultural self-employment, sales of natural resources, and pensions and remittances. Since smallholders often consume much of what they grow, agricultural production income includes the imputed value of food grown and consumed by the household. All variables used in the analysis are population-weighted and 2008 income figures were converted to 2005 values using regional consumer price indexes provided by the Mozambican National Institute of Statistics (INE, 2014). We use adult-equivalent (AE) adjusted incomes to control for household size. All decomposition analyses were carried out using the Distributive Analysis Stata package (Duclos & Abdelkrim, 2007).

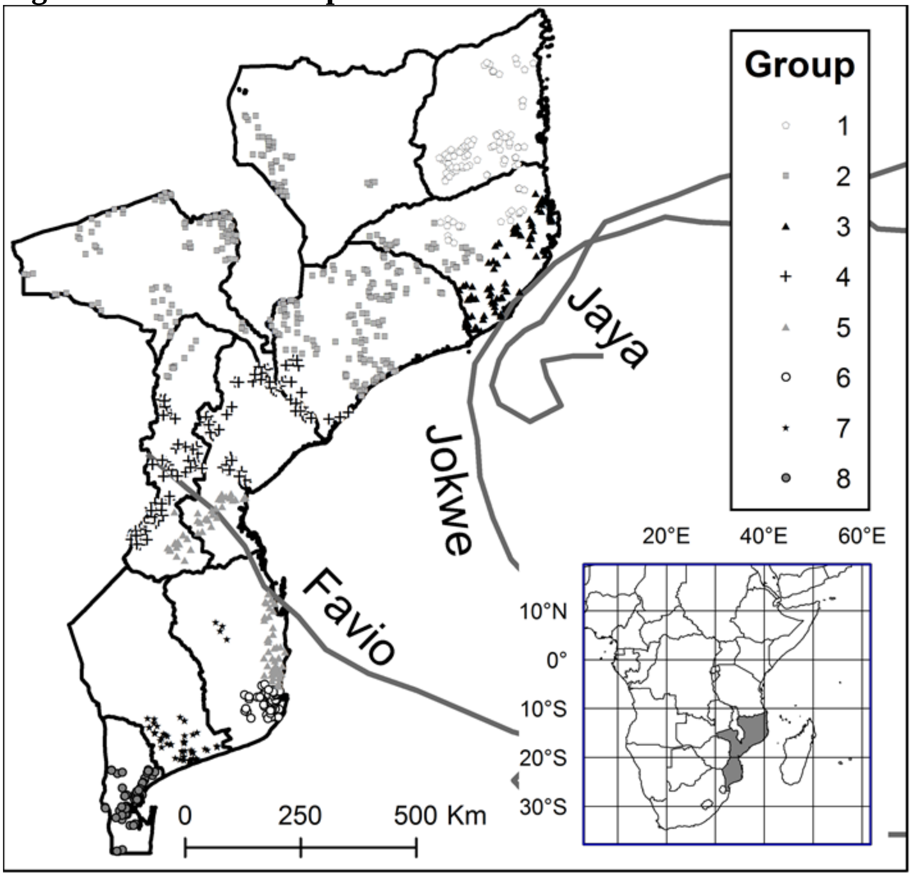
Constructing the Climatology and Grouping Villages by Rainfall Patterns

To examine rainfall, we acquired data from the Tropical Rainfall Measuring Mission (TRMM) 3B43 product (Huffman et al., 2007). These satellite-based estimates are gauge-corrected and available monthly at a spatial resolution of 0.25° x 0.25°. This represents 1088 grid cells over Mozambique. Utilizing a GIS, data from January 1998 – December 2013 are averaged to create a 16-year climatology for each month. The main growing season spans October – March in the south, and November – March in the north. Thus, we calculated the percentage of normal monthly rainfall received in each grid cell for these months during the 2005-2006, 2006-2007, and 2007-2008 agricultural seasons (hereafter referred to as Seasons 1, 2, and 3, respectively) that occurred between the two TIA surveys. Each village then received the value of the TRMM cell within which it was located.

We utilized rainfall totals and estimates of damaging winds to identify villages most likely to have experienced impacts from tropical cyclones (TCs). Track data from the International Best Track Archive for Climate Stewardship (IBTrACS) (Knapp et al., 2010) were plotted in the GIS to identify TCs located within 100 km of Mozambique. Data from the TRMM 3B42 product contain rain rate estimates every three hours at the 0.25° x 0.25° spatial resolution. These data were visually inspected to determine which TCs produced rainfall over Mozambique and the start and end times defining each event. Data between these times were used to calculate the storm-total rainfall for each village. Cyclones Favio (2007), Jaya (2007), and Jokwe (2008) produced at least 150 mm of rainfall in multiple villages. To determine the possible extent of wind damage during the landfalls of Favio and Jokwe, the radius of damaging-force winds (26 m s^{-1}) every six hours was obtained from IBTrACS. Villages located within this distance from the track were identified in the GIS.

Our economic analysis requires that we group villages receiving similar rainfall patterns to examine the impacts of rainfall variability and extreme events on regional inequality and polarization. The 63 villages receiving 150 mm of rainfall and/or located within the damaging-wind radius of Favio comprised one group. Multiple villages were affected by both Jaya and Jokwe, so these were combined into one group of 57 villages. Two hierarchical cluster analyses were performed on the remaining 554 villages, one for the 142 southern villages that included the percent of normal rainfall for October-March for each agricultural season, and one for the remaining 412 villages utilizing the percent of normal rainfall for November-March. Three clusters emerged from each of these analyses, yielding eight groups in total (See Figure 1).

Figure 1 Weather Groups



Gini Decomposition

To analyze changes in regional inequality, we conduct a decomposition of the Gini index by population subgroups (i.e., our eight weather groups) for 2005 and 2008. The Gini index decomposition equation can be expressed as follows:

$$I = \underbrace{\sum_{g=1}^{G} \phi_g \varphi_g I_g}_{Within} + \underbrace{\bar{I}}_{Between} + \underbrace{\bar{R}}_{Overlap} \quad (1)$$

Where: I = The Gini index; G = Total population of subgroups g; ϕg = Population share of group g; φg = Income share of group g; Ig = Gini index for group g; $\bar{I}$ = Between-group inequality (when each individual is assumed to have the average income of its group);

and $\overline{R}$ = The residual from overlapping income levels across groups (e.g., overlap inequality).

As presented in equation (1), the Gini index coefficient for the entire sample is comprised of three components: within-group inequality, between-group inequality, and overlap inequality. As described by Abdelkrim (2008), the contribution of between-group inequality for the full sample is calculated as a function of the differences in group mean incomes, each group's population and income share, and number of groups included in the analysis. Overlap inequality accounts for the degree to which similar income levels are found across the different groupings. The more income levels within the groups resemble one another, the higher the value for overlap inequality. The Gini decomposition method also estimates the magnitude, in both absolute and relative terms, of the contribution of each group to within-group inequality.

DER Polarization Index Decomposition

For our analysis of regional polarization, we use the Duclos, Esteban and Ray (DER) polarization index (Duclos et al. 2004) as it can be decomposed in a manner similar to the Gini index. The DER index accounts for the degree to which similar incomes cluster along an income distribution, as well as the spread between incomes. Thus the examination of polarization complements our analysis of the Gini coefficient. Like the Gini, the DER coefficient values range from 0 to 1, with higher values denoting more polarization.[2]

Abdelkrim (2008) illustrates that the DER index can be decomposed as follows:

[2] The DER coefficient equals 0 when all households receive the same income, and takes the value of 1 when there are two equally sized groups, one on each extreme end of the distribution.

$$P(\alpha) = \underbrace{\sum_{g=1}^{G} \phi_g{}^{1+\alpha} \varphi_g{}^{1-\alpha} R_g P_g}_{Within} + \underbrace{\overline{P}}_{Between} \tag{2}$$

Where:

$$R_g = \frac{\int a_g(x)\pi_g(x) f(x)^{1+\alpha} dx}{\varphi_g \int a_g(x) f_g(x)^{1+\alpha} dx} \tag{3}$$

Where: G = Total population of subgroups g; a = A normative parameter that expresses the sensitivity of the index to inequality ϵ [.25-1]; ϕ_g = Population share of group g; Φ_g = Income share of group g; P_g = DER index for group g; π_g = Local proportion of households belonging to group g and having income x; $f(x)^{1+\alpha}$ = Density function of income x (i.e., identification effect); $f(x)_g{}^{1+\alpha}$ = Density function of income x for group g (i.e., identification effect of group g); $a_g(x)$ = The absolute distance from income x and other incomes in group g (i.e., alienation effect of group g; equal to the group-level Gini coefficient); dx = Differential distance or spread of income x from the median.

The DER index also measures the magnitude of relative deprivation and surplus income among households within a group. The relative deprivation of a household with income x as compared to that of a household with income y can be expressed as follows:

$$\tau(x, y) = (y - x)_+ = \left\langle \begin{matrix} y - x & if & x < y \\ 0 & & otherwise \end{matrix} \right. \tag{4}$$

Where the deprivation of a household with income x is equal to:

$$\delta(x) = \int \tau(x, y) f(y) dy \tag{5}$$

And the expected surplus of a household with income x is equal to:

$$\sigma(x) = \int \tau(y,x) f(y) dy \tag{6}$$

The deficit and surplus components of groups can be estimated as follows:

$$P = \sum_{g=1}^{G} \frac{1}{\mu^{1-\alpha}} \int ([\delta(x) + \sigma(x)] f(x)^{\alpha}) \pi_g(x) f(x) d(x) dx$$

$$= \sum_{g=1}^{G} D_g + S_g \tag{7}$$

Where μ= the mean income of the population weighted by the chosen alpha parameter.

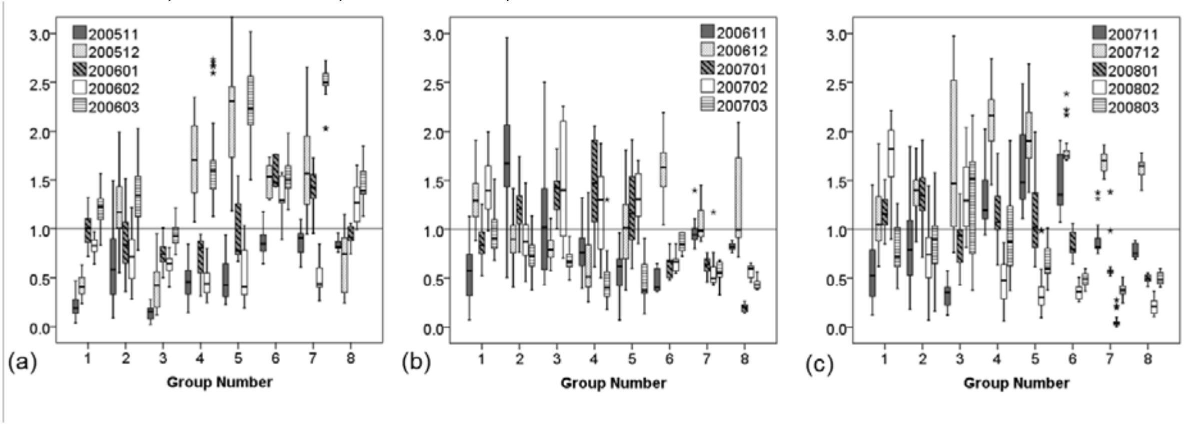
If a particular group is composed of a significant proportion of poor households relative to the group mean, the ratio D_g/S_g will be relatively higher compared to groups with larger concentrations of wealthier households. Using this methodology, changes in polarization can also be analyzed based on the direction of income shifts along the distribution over time.

3 RESULTS

Regional Groupings by Shared Weather Patterns

Each of our eight weather groups represents a distinct weather pattern over the time period of the study. Figure 2a, 2b, and 2c illustrates the rainfall variability for each group for Seasons 1, 2, and 3, respectively. However, we find that each group can be broadly classified into one of three categories: those experiencing near-normal rainfall, those experiencing a cyclone or flooding event, and those experiencing progressively worsening drought conditions. All groups that experience a form of extreme weather are used to test our first hypothesis. The groups with near-normal weather relate to our second hypothesis. Adverse weather conditions can negatively impact agricultural yields in any month during the growing season. However, in describing the weather groups, we emphasis conditions in February-April when many areas experienced extreme events during our study period. Maize, Mozambique's staple food crop, tassels in February making it vulnerable to dry conditions and extreme wind events. The harvest takes place in March and April, making these months particularly vulnerable to extreme wet events.

Figure 2 Boxplots Depicting Proportion of Normal Rainfall for Each Group November – March in a) Season 1, b) Season 2, c) Season 3



Near-normal Rainfall Patterns

Groups 1 and 2 span the northern and western portions of Mozambique and received the most normal rainfall. Group 1's 76 villages were somewhat drier in Season 1 with rainfall 50% of normal in the first two months. Seasons 2 and 3 averaged close to normal with November being the driest month and February the wettest month. Although the large geographic spread amongst the 227 villages in Group 2 leads to high variation in rainfall totals for many of the months, rainfall fell within 125% of normal on average during nine of the fifteen study months.

Tropical Cyclone and Flood Affected Areas

Group 3 contains locations affected by cyclones (Jaya and Jokwe) in Seasons 2 and 3. Although Jaya remained offshore, 57 villages received more than 150 mm of rainfall from the event during April, 2007 and rainfall was more than 300% of normal. Jokwe made landfall on March 8, 2008 with maximum sustained winds of 56 m s^{-1}. Damaging-force winds extended outwards 95 km from its center. Only 10 villages received more than 150 mm of rainfall, but there was wind damage to infrastructure (Fitchett and Grab, 2014), and extensive crop damage (Hanlon 2009). Reliefweb (2008) estimates that 60,000 people were affected by Jokwe, which caused over $8 million dollars in damage.

Group 4 contains 109 villages, some of which were affected by the flooding of the Zambezi River in Seasons 2 and 3. The Zambezi burst its banks in February 2007 and again in January of 2008, and the consecutive events contributed to widespread damages and hardship (Brida et al., 2013). More than 330,000 people in Mozambique were estimated to have been affected by the 2007 flood (USAID 2007) (Stal 2011) and more than 250,000 were affected in 2008 (ReliefWeb 2008). Our rainfall analysis shows that rainfall was variable in Season 1 with November and February averaging 50% of normal and December and March 175% of normal. Season 2 was closer to normal with most rainfall occurring in January and February. The highest average rainfall in Season 3 across the study region occurred for Group 4 in December in conjunction with the flooding previously mentioned. Rainfall decreased to 50% of normal during February 2008.

The villages affected by Favio in Season 2 comprise Group 5. Favio made landfall on February 22, 2007 in Inhambane Province and tracked inland (Figure 1). Maximum sustained winds were estimated at 51 m s^{-1}. Fitchett and Grab (2014) estimated that Favio caused $71 million in damage, partly due to the destruction of infrastructure in Vilanculos, a popular tourism destination in Mozambique. According to Cosgrave et al. (2007), fast winds caused most of this damage, affecting both structures and crops. Using the IBTrACS data, we estimated damaging-force winds to extend 110 km outwards from the center near landfall time, decreasing to 55 km twelve hours later. According to USAID (2007), 162,770 people were affected by Favio. Our rainfall analysis supports the observation that excessive rainfall was not the main impact of Favio as only 18 villages received more than 150 mm of rain, and average rainfall over the group was under 150% of normal. Season 3 started off much wetter than normal but rainfall fell below normal in February and March.

Progressively Worsening Drought Conditions

Season 1 of our study was a break from the nearly continuous drought experienced in the previous five years (FEWSNET, 2006; Brida et al., 2013). Rainfall in the southern provinces was near to above normal for most of Season 1. Group 6 contains 44 villages located in Inhambane Province outside of the areas affected by Favio, and experienced rainfall averaging 150% of normal for most of the season. The pattern was a little different for the 46 villages of Group 7 that were primarily located in Gaza Province as February was fairly dry. Rainfall then increased in March to 250% of normal. Rainfall was closer to normal for Group 8, encompassing 52 villages in Maputo Province.

In Season 2 rainfall ranged from 50-80% of normal during most months for these three groups, with more rainfall occurring in December. The driest month of the season occurred in Group 8 where rainfall averaged 25% of normal during January. The presence of drought in southern Mozambique was confirmed by ReliefWeb (2008). Rainfall was even lower for all three groups during Season 3, with three consecutive months experiencing 50% of normal values. The most extreme case of dry conditions over the study period occurred during February in Group 7, with most villages receiving less than 5% of normal rainfall (as compared with 40% and 25%, for Groups 6 and 8, respectively).

Decomposition of Gini and DER Indexes for Total Income across Rainfall Clusters

Table 1 provides descriptive statistics on income and poverty levels of our eight weather groups. In six cases, mean incomes declined between 2005-2008, and the magnitude of reductions ranged from 41% in Group 3 to 20% in Group 5. The results are statistically significant for four of these groups, included the two which were impacted by cyclones. Using the $1.25/day, purchasing power threshold, our analysis indicates high poverty headcounts for both years; ranging from 87-60% in 2005 and 92-58% in 2008. The poverty headcount rates differed by weather group; X^2(7, N = 2603) = 101, $p < .001$ and X^2 (7, N = 3321) = 104, $p < .001$ for 2005 and 2008, respectively.

Tables 2 and 3 present the results of our decomposition analysis of the Gini index for the years 2005 and 2008. Tables 4 and 5 present our findings for the decomposition of the DER polarization index over the same time period.

The Gini index for our sample of TIA households indicates high levels of inequality for both years and, similar to Arndt et al. (2012) and Geisbert and Schindler (2012), we find the coefficient remains largely unchanged (0.62 and 0.61 for 2005 and 2008, respectively). Arndt et al. (2012).) Overlap inequality makes the largest contribution to the overall Gini coefficient – at or above 50% in both years – which indicates that wealth and poverty are highly dispersed across the country.[3] This comports with other research that indicates a very high degree of local-level (See Heltberg *et al.* (2001) and Simler and Nhate (2002)).

Polarization, as measured by the DER index, also remains unchanged at 0.314. The polarization estimate, like the Gini coefficient, is very high. For both decomposition analyses,

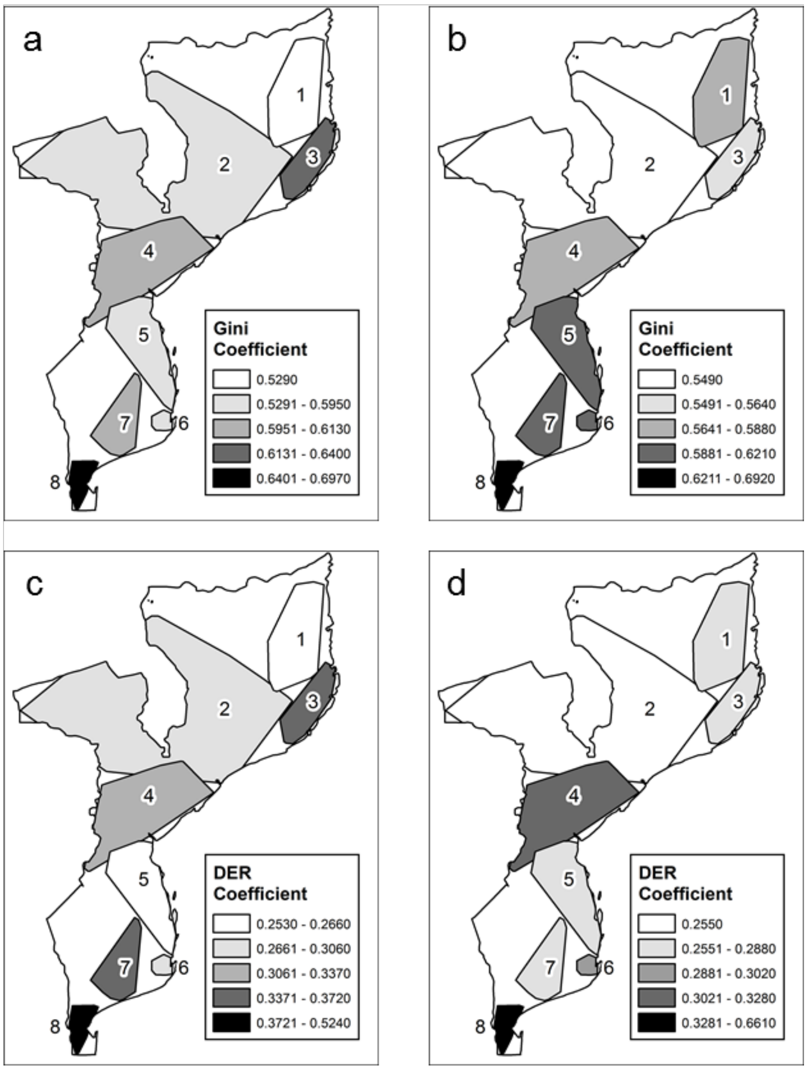
[3] The TIA in 2005 and 2008 primarily sampled rural, agricultural households and did not include households from Maputo City, so it does not capture the high spatial concentration of wealth in the nation's capital city.

our use of eight groups and the resulting low population share of each group limits the degree to which within-group dynamics alter the coefficients for the full sample.

High Variability at the Group-level

The stable Gini and DER coefficients for our full sample mask substantial changes in inequality and polarization within our eight weather groups. These shifts demonstrate a high degree of regional variability during the time period of the study (See Figure 3, Table 7). With the exception of Group 8, the group rankings for inequality change between years in all cases, indicating a high degree of volatility for inequality at the group level. These shifts are even more pronounced for polarization. Even in cases when group rankings based on absolute values of inequality and polarization remain similar, we still witness substantial differences between years as measured by percentage change in the Gini and DER coefficients, and the D/S ratio.

Figure 3 Inequality and Polarization Values for Weather Groups - a) Gini coefficients in 2005, b) Gini Coefficients in 2008, c) DER Coefficients in 2005, and d) DER coefficients in 2008



Three distinct patterns emerge in our analysis of regional inequality and polarization among our weather groups (See Figure 4). In the first scenario, both inequality and polarization increase. In the second scenario, the two measures decrease. These patterns cut across areas that experienced near-normal weather, cyclones and flooding, and progressively worsening drought conditions. Only in one case, Group 8, do inequality and polarization move in different directions. Our results correspond with the findings of Zhang and Kanbur (2001) that shifts in inequality and polarization are highly correlated. In our presentation of the results that follows we focus on the considerable variation between groups in the direction and magnitude of change in inequality and polarization.

Figure 4 Scenarios of Regional Inequality and Polarization

Scenario 1	Scenario 2	Scenario 3
Inequality Increases	Inequality Decreases	Inequality Decreases
Polarization Increases	Polarization Decreases	Polarization Increases
Group 1↓* Group 5↓¥ Group 6↑§ *Group 7*↓§	*Group 2*↑* *Group 3*↓¥ *Group 4*↑¥	*Group 8*↓§

↓ = incomes shift downward towards lower end of income distribution
↑ = incomes shift upward towards the upper in of the income distribution
* = Near-normal rainfall group; ¥ = TC/Flooding group; § = Progressively dry group

Scenario 1: Increasing Inequality and Polarization

For Groups 1, 5, 6, and 7, incomes become more dispersed from the mean and more concentrated at opposite ends of the distribution. This indicates that the gap between rich and poor households increased, and clusters along the distribution were more sharply defined (e.g., spikier, with higher peaks), particularly along the extreme ends of the distribution. In three of the cases where both inequality and polarization increase, the groups (1, 5, and 6) had the lowest levels for both measures in 2005. Group 1 experiences the greatest increases in inequality and polarization of all groups. The D/S ratio, which roughly measures where the greatest concentration of incomes fall along the distribution relative to the group mean, also experiences the second largest decline (38%). This suggests that incomes became particularly more concentrated towards the lower half of the distribution.

Groups 5 and 6 show an increase in inequality and polarization roughly half that experienced by Group 1. This suggests that the distribution of the groups also became characterised by higher peaks, but the increase was less pronounced. The change in D/S ratio indicates that the proportion of higher-income households increases in Group 6, suggesting income levels shifted towards the upper end of the distribution. In contrast, the change in D/S ratio for Group 5 indicates a higher share of low-income households in 2008, and incomes generally moved lower down the distribution.

In Group 7, inequality slightly increases by 1% but polarization rises more substantially. This indicates that incomes become a little more spread out from the mean, but that clusters of similar incomes along the distribution become much more populated with higher peaks. Despite the small percentage increase in inequality, this group has the second highest Gini coefficient in 2008. The change in D/S ratio suggests an increasing proportion of household incomes situated at the lower end of the distribution.

Scenario 2: Decreasing Inequality and Polarization

Groups 2, 3, and 4 all experience a reduction in both inequality and polarization levels. These groups have less sharply defined clusters of rich and poor households along the distribution in 2008, and incomes converge more towards the mean. In other words, income clusters flatten at the extreme ends of the distribution and resemble wider lumps as opposed to narrow spikes. Group 3 experiences the greatest decrease in inequality and polarization of all groups, followed by Group 2. Group 3 also has the greatest increase its proportion of households clustering in the lower end of the distribution, as measured by the D/S ratio. In 2008, this group has the highest concentration of poor households relative to its mean.

In Groups 2 and 4 the Gini coefficient decreases by similar percentages. However, polarization in Group 2 decreases almost five times more. This suggests that Group 2's distribution is characterized by a greater reduction in the concentration of incomes at the tail ends of the distribution. For both groups, the D/S ratio suggests that incomes shift upward along the distribution, increasing the proportion of relatively wealthier households.

Scenario 3: Decreasing Inequality and Increasing Polarization

Group 8, comprised of villages in southern Maputo Province, is the only area that exhibits opposite trends in inequality and polarization over the time period of the study. Inequality decreases, but by less than 1%, while polarization experience the largest increase of any group. Groups 8 had the highest levels of inequality and polarization in both 2005 and 2008. The minimal change in inequality, large increase in polarization, and the smallest change in the D/S ratio indicates that the gap between the wealthy and the poor remained stable, but incomes became more concentrated at each end of the distribution, with little change in the proportion of wealthier or poorer households.

Distribution Dynamics in the Context of Weather-related Shocks

Contrary to widely-held assumptions in the literature, we no find little evidence to suggest a relationship between initial levels of inequality in a group and the degree or direction of changes in the aftermath of an extreme weather event. The same is true with polarization. This suggests that other factors besides intra-regional economic disparities mediate the effects of weather on income inequality and economic polarization, a finding that is consistent with several empirical case studies that highlight the importance of local collective action and social networks in climate vulnerability and adaptation (Rodima-Taylor, 2012; Scheffran et al., 2012).

The results of the analysis support our initial hypotheses in five of the eight weather groups. Group 2 experiences near-normal weather and, as expected, incomes converge, becoming more evenly distributed across the income distribution. In four other cases, extreme weather events correspond with increasing distance between incomes and more pronounced concentrations along the distribution. This happens in the Favio-impacted region (Group 5).

The same pattern is apparent in regions characterized by progressively worsening drought conditions (Groups 6, 7 and 8). Although inequality experiences a very slight reduction for Group 8, the substantial increase in polarization suggests that households in the group had varying abilities to adapt to poor weather conditions. The concurrent economic shocks associated with rapidly rising food and fuel prices most likely compounded weather-related effects on inequality and polarization, as is generally expected. We therefore focus on Groups 1, 3, and 4 in following section, given our findings in these cases lead us to reject our hypotheses, and suggest that standard understandings of the relationship between weather conditions, economic change, and income disparities are incomplete.

To examine whether trends in increasing income inequality and polarization continue for the 2008 and 2012 time period, we conducted Gini and DER decompositions for this period. However, we do not report these table and the results must be interpreted with caution because our eight groups are not unified by similar weather patterns during 2008-2012, a period when two major cyclones, Dando and Funso, made landfall in different regions of the country.[4] We find that Groups 1, 4, 5, and 7 experience further increases in income disparities and polarization, indicating that these trends continue in the short- to medium-term.

In Group 3, income inequality and polarization increase, but remain lower than 2005 levels, suggesting that some households improve their economic position to some degree but not enough to recover from the weather-related shocks associated with cyclones Jaya and Jokwe. The fact that some Group 3 households were affected by tropical cyclones Dando and Funso in 2012 while others were not likely contributes to the reversal in inequality and polarization levels. Households which experienced the additional weather-related shocks would be expected to suffer greater loss of incomes than the others.

[4] The Gini and DER decomposition results using the TIA 2012 data (MINAG 2012) are available from the authors upon request. The unifying weather patterns changed substantially between 2005-2008 and 2008-2012 making a detailed analysis of income distributions over this longer time period beyond the scope of this paper.

Groups 6 and 8 experience decreases in inequality between 2008-2012, but as with Group 3, the Gini coefficients do not exceed 2005 levels. However, Group 6 is characterized by higher levels of polarization in 2012 as compared to 2005, while the opposite effect occurs in Group 8. Several Group 8 villages were affected by Dando while those in Group 6 were not, another indication that extreme events in 2008-2012 likely affect trends in income distributions. In Group 2, inequality and polarization both decrease, and the Gini and DER coefficients are lower than 2005 levels, suggesting a reversal of the trend we find for 2005-2008. Since neither Dando nor Funso affected this area, this finding points to the need for future analysis of rainfall patterns and economic shocks in the region following 2008.

In sum, our findings suggest that weather groups impacted by extreme events such as cyclones and flooding tend to exhibit sustained trends over the 2005-2012 period, while changes in incomes distributions in areas characterized by drought conditions or near-normal weather appear more variable. This suggests that economic and weather-related shocks during the 2008-2012 period merit future research to better examine the enduring nature of shocks on income distributions and how additional shocks contribute to changing patterns of inequality and polarization at the sub-national level.

4 DISCUSSION

Declining Inequality and Polarization in the Aftermath of Weather-related Shocks

Contrary to expectations, inequality and polarization decrease in two regions that experienced extreme weather events. However, the ways in which the income distribution shifts in some areas suggests that decreasing inequality and polarization should not necessarily be interpreted as an indication of better ability to mitigate the effects of extreme weather.

In the case of Group 3 where households were impacted by Jaya and Jokwe, our findings suggest that a widespread increase in poverty drives the convergence in incomes. Moreover, this shift takes place in an area already characterized by high poverty in 2005. Several factors contributed to the dramatic decline in incomes. First, households were affected by two cyclones (March 2008 and April 2007). This had a negative impact on crop yields for two consecutive years since both cyclones occurred during the harvesting period Crop income accounted for more than 70% of the total income in 2008 for households in Group 3, suggesting high vulnerability to extreme weather events.

Second, Jokwe also disrupted other key economic activities in the area: cashew bean farming and fishing. Jokwe destroyed an estimated two million cashew trees, damaged eight cashew processing plants (Macauhub, 2008; Reliefweb, 2008c), and damaged numerous fishing boats (Reliefweb, 2008d). The area also experienced an outbreak of the brown streak virus disease that reduced cassava harvests (FewsNet, 2009). Given the low initial income levels (even for relatively better-off households), the decrease in inequality and polarization suggest that these series of shocks triggered severe economic setbacks for some households that contributed to or created what Carter et al. (2007) refer to as a poverty trap. Given our findings, it is possible households fell below a minimum asset threshold below which they are unable to invest in human and physical capital and subsequently face significant barriers to lift themselves out of poverty.

We find little evidence that wealthier households in this area were able to better mitigate the negative impacts of a cyclone substantially better than lower-income households, at least in the short term. The TIA data indicate that households in Group 3 did not experience an increase in income share from self-employment activities and salaries despite the fact this area is located in the Nacala Development Corridor (*Corredor de Desenvolvimento de Nacala*, CDN). The CDN made significant investments in roads, railways and other key infrastructure during the time period of the study, and those investments should theoretically increase more formal employment opportunities in the area. This suggests that households were generally unable to increase their participation in higher-earning, formal activities, and that their inability to do so had inequality-dampening effects.

The drivers of convergence appear to differ in Group 4. Although this group includes households impacted by the Zambezi Floods of 2007 and 2008, we find an increase in the proportion of higher income households. The median income increases by 4%, further signifying that poorer households became slightly better off on average. Yet the mean income decreases by 3%, pointing to a modest decline for households at the upper end of the distribution.

Several factors may influence why we see this pattern of convergence (e.g., the income floor rising, while the ceiling falls) in Group 4. One possibility concerns the composition of the 2008 TIA sample. Stal (2011) finds that many poorer households were relocated after the floods and some did not move back to the area, which could result in a fewer poor households in Group 4 at the time of the 2008 survey. Declining levels of wealth could also be partly the result of disaster relief efforts. Brouwer and Nhassengo (2006) find that wealthier households were made worse off vis a vis poorer ones in the aftermath of the Mozambican floods of 2000 and 2001 off since they did not receive as much post-flood recovery assistance and had to draw on their own financial assets and personal support networks. However, the TIA data in not longitudinal at the household-level and collect very limited information on the receipt of disaster recovery assistance which prevents us from empirically testing for these effects,

Another possible explanation for higher incomes among poorer households involves the expansion of the off-farm sector, especially for unskilled labor. Group 4 is located in an area that experienced considerable levels of investment during the study period, including the rehabilitation and construction of roads, railways, and bridges, including the Armando Guebuza Bridge over the Zambezi River, and the Beira-Marrmeu railway line which opened in 2008. These projects led to higher employment opportunities, particularly temporary construction work, during the 2007/2008 agricultural season. Road construction projects in particular tend to be labor-intensive, so smallholder farmers have more access to off-farm income that can be used to mitigate the effects of climate variability. The Marromeu sugar factory also reopened in this area during the time period of the study. Wage income share grew by 5.8% between 2005 and 2008 in Group 4, the largest increase of any weather group, and lends some support to the possibility that relatively good labor market access helped some households recover from the floods. Thus, our findings in this specific case correspond to Giesbert and Schindler's (2012) observation that the economic position of households in rural Mozambique are converging, but at near-poverty levels.

Good Weather and Increasing Inequality and Polarization

The finding that Group 1 experienced the largest increases in inequality and polarization goes against our second hypothesis, given that households in this area experienced relatively good weather with rainfall generally near-normal levels for all three years. Increasing reliance on wage income appears to be one inequality-enhancing factor. TIA data show that the share of wage income to total income was lowest in Group 1 in 2005, but it almost doubled by 2008. The increase in wage income is most likely driven by the these construction project and the recent boom observed in oil and natural gas industries in Cabo Delgado. However, the poor may not be able to gain from the growth in extractive industries due to very low levels of education or locally-mediated access that privileges more influential households or those belonging to more dominant groups.

Physical factors may also account for rising inequality and polarization. Households in Group 1 are located in districts of lower altitude and higher temperatures, which means more evapotranspiration and more need for irrigation. However, only 2.7% used irrigation in 2005 and 2008 (TIA 2005, 2008). Indeed we find both change in crop income and maize production (per AE, per hectare) to be positively correlated with higher elevations in our sample with $r(6683) = .09$, $p < .01$ and $r(2134) = .25$, $p < .01$, respectively. In addition, many households in Group 1 experienced drier than normal Novembers for all three years, which could have led to late planting and a subsequent negative impact on yields. The use of improved agricultural technologies is also very low in Group 1 relative to our other study area that received good weather (Group 2). So near-normal rainfall may translate into better crop yields, but limited institutional support (e.g., reduction in the coverage of extension services and access to price information, extremely limited access to credit, and lack of market access) (Cunguara et al. 2013) prevent many farmers from benefiting economically.

5 CONCLUSION

By integrating analytical techniques from climatology and economic geography, we illustrate how mixed-methods and interdisciplinary approaches can improve understandings of weather-related effects on socio-economic outcomes in rural societies. Our study of Mozambique finds that household groupings unified by similar weather conditions still exhibit very different patterns of changing regional inequality and polarization. Inequality is repeatedly described as a both a consequence and a driver of differential vulnerability to climate-related disasters (IPCC, 2014a, 2014b). The findings for five of our eight weather groups lend some support to this widely held assumption in the literature. In these cases, as hypothesized, incomes in regions with adverse weather conditions experience increasing inequities and more pronounced divisions between rich and poor households. Conversely, good weather can contribute to greater equity and less concentration of wealth and poverty. Moreover, we find some evidence to suggest that the extreme wet events lead to more enduring patterns on income distributions. By examining underlying dynamics of how the distributions change over time, we find that increasing inequality and polarization can occur as regions gain higher proportions of wealthier households. In other cases, increasing inequities happen as incomes become more concentrated at the lower ends of the distribution. A preliminary analysis of distributional change over 2008-2012 suggests that these patterns hold in the longer-term, although findings must be interpreted with caution, given that our groups were unified by weather patterns that occurred between 2005-2008 and do not account for subsequent weather shocks.

The results of our analysis of sub-national dynamics in rural Mozambique also indicate that inequality and polarization can decline in the aftermath of an extreme event, and increase even where the weather is relatively good. These patterns all occur in the context of macroeconomic shocks that had similar effects across the country (i.e., increasing food and fuel prices) and are often associated with worsening poverty and exacerbating vulnerability to extreme events. We caution against simplistic interpretations that associate lower levels of inequality and polarization as positive signs of development. If worsening poverty for the majority of households or convergence at near-poverty income levels drives reductions in regional income disparities and polarization, this can also signal an extreme form of vulnerability at both the household and the community level. Both situations could potentially erode social networks and systems of reciprocity, contributing to situations in which communities have limited internal resources to help those most impacted by shocks. In such cases, communities and regions may become increasingly vulnerability and more dependent on external assistance. Taken together, our findings suggest that the adaptive capacity to deal with extreme weather (or the ability to benefit from favorable weather conditions) are greatly influenced by highly localized, contextual factors that merit more detailed attention in future studies of the mechanisms driving regional disparities.

REFERENCES

Abdelkrim, A. (2008). *On the Decomposition of Polarization Indices: Illustrations with Chinese and Nigerian Household Surveys*. Working Paper 08-06, CIRPEE: Quebec, Canada. Retrieved from: http://www.cirpee.org/fileadmin/documents/Cahiers_2008/CIRPEE08-06.pdf

Ahmed, S., Diffenbaugh, N., & Hertel, T. (2009). Climate volatility deepens poverty and vulnerability in developing countries. *Environmental Research Letters*, 4034004. doi:10.1088/1748-9326/4/3/034004

Arndt, C., Strzepeck, K, Tarp, F., Thurlow, J, Fant, C. & Writght, L. (2010). Adapting to climate change: an integrated biophysical and economic assessment for Mozambique. *Integrated Research System for Sustainability Science*, 10.1007/s11625-010-0118-9

Arndt, C., Hussain, M.A., Jones, E.S., Nhate, V., Tarp, F. & Thurlow, J. (2012). Explaining the evolution of poverty. The case of Mozambique. *American Journal of Agricultural Economics*, 94, 854-872.

Brida A-B, Owiyo T & Sokona Y (2013). Loss and damage from the double blow of flood and drought in Mozambique. *International Journal of Global Warming*, 5, 514-531.

Brouwer, R., & Nhassengo, J. (2006). About bridges and bonds: Community responses to the 2000 floods in Mabalane District, Mozambique. *Disasters*, 30, 234-255.

Carter, M., Little, P., Mogues, T., & Negatu, W. (2007). Poverty traps and natural disasters in Ethiopia and Honduras. *World Development*, 35, 835-856.

Corina, G.A. (ed) (2004). *Inequality, growth, and poverty in an era of liberalization and globalization*. Oxford: Oxford University Press.

Cosgrave J, Gonçalves C, Martyris D, Polastro R & Sikumba-Dils M (2007). *Inter-agency real-time evaluation of the response to the February 2007 floods and cyclone in Mozambique*. Report for UN System.

Cunguara, B., (2008). *Pathways out of poverty in rural Mozambique*. MSc Thesis. East Lansing: Michigan State University.

Cunguara, B. & Hanlon, J. (2012). Whose Wealth Is It Anyway? Mozambique's Outstanding Economic Growth with Worsening Rural Poverty. *Development and Change*, 43, 623-647.DOI: 10.1111/j.1467-7660.2012.01779.x.

Cunguara, B., Langyintuo, A., & Darnhofer, I., (2011). The role of nonfarm income in coping with the effects of drought in southern Mozambique. *Agricultural Economics* 42, 701-713.

Cunguara, B., Garrett, J., Donovan, C., & Cássimo, C. (2013). *Análise situacional, construangimentos e oportunidades para o crescimento agrário em Moçambique*. Relatório de Pesquisa #73P, Maputo: Ministério da Agricultura.

DNEAP/MPD. (2010). *Poverty and wellbeing in Mozambique: Third national poverty assessment*. National Directorate of Studies and Policy Analysis, Maputo. Retrieved at: http://aec.msu.edu/%5C/fs2/mozambique/caadp/THIRD_NATIONAL_POVERTY_ASSESSMENT_october1.pdf.

Duclos, J-Y., & Abdelkrim, A. (2008). *On the Decomposition of Polarization Indices: Illustrations with Chinese and Nigerian Household Surveys*. Working Paper 08-06, CIRPEE: Quebec, Canada. Retrieved from: http://www.cirpee.org/fileadmin/documents/Cahiers_2008/CIRPEE08-06.pdf

, A. (2007). *DASP: Distributive Analysis Stata Package*. PEP, World Bank, UNDP and Université Laval. Retrieved at: http://dasp.ecn.ulaval.ca/.

Duclos, J-Y., Esteban, J. & Ray, D. (2004). Polarization: Concepts, Measurement, Estimation. *Econometrica*, 72(6), 1737–1772. DOI: 10.1111/j.1468-0262.2004.00552.x.

FEWSNET. (2006). *Mozambique food security update*. http://www.fews.net/ Accessed 7 August 2014.

FEWSNET. (2009). *Mozambique food security update*. Retrieved at: http://www.fews.net/sites/default/files/documents/reports/Mozambique_2009_02%20final.pdf

Fitchett JM & Grab SW (2014). A 66-year tropical cyclone record for south‐ east Africa: temporal trends in a global context. *International Journal of Climatology* doi:10.1002/joc.3932

Giesbert, L. & Schindler, K. (2012). Assests, shocks, and poverty traps in rural Mozambique. *World Development*, 40, 1584-1609.

Grineski, S.E., Collins, T.W., Ford, P., Fitzgerald, R., Aldouri, R., Velázquez-Angulo, G., Aguilar, M.L.R., & Lu, D. Climate change and environmental injustice in a bi-national context. *Applied Geography*, 33, 25-35.

GOM. (2001). *Action plan for the reduction of absolute poverty (2001-2005)*. Maputo, Mozambique: Government of Mozambique.

GOM. (2006). *Action plan for the reduction of absolute poverty (2006-2009)*. Maputo, Mozambique: Government of Mozambique.

GOM. (2011). *Action Plan for the Reduction of Absolute Poverty (2011–2014)*. Government of Mozambique: Maputo, Mozambique.

Hanlon, J. (2009). Mozambique: The Panic and Rage of the Poor. *Review of African Political Economy*, 36, 125-130. doi:10.1080/03056240902919900

Hanlon, J., & Smart, T. (2008). *Do bicycles equal development in Mozambique?* Woodbridge, Suffolk, UK: James Currey.

Heltberg, R., Simler, K., & Tarp, F. (2001). *Public Spending and Poverty in Mozambique*. WIDER Discussion Paper No. 2001/63. United Nations University: Tokyo. Retrieved at: file:///C:/Users/juliesilva/Downloads/dp2001-63_1.pdf

INE. (2014). Consumer Price Index. Maputo: National Institute of Statistics. Intergovernmental Panel on Climate Change (IPCC). *Climate change 2007: Impacts, adaptation and vulnerability*. Cambridge University Press, Cambridge, 2007, 976.

IPCC. (2007). *Climate change 2007: Impacts, adaptation and vulnerability*. Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

IPCC. (2014a). *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York.

IPCC. (2014b). *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York.

Jones, A., LaFleur, V., & Purvis, N. (2009). Double jeopardy: what the climate crisis means for the poor. In: Brainard, L, Jones, A, & Purvis, N, eds. *Climate Change and Global Poverty: A Billion Lives in the Balance*. Washington, DC: The Brookings Institution, 10–42.

Knapp K.R., Kruk, M.C., Levinson, D.H. Diamond, H.J., & Neumann, C.J. (2010). The International Best Track Archive for Climate Stewardship (IBTrACS): unifying tropical cyclone data. Bull Amer Meteor Soc 91:363-376. doi:doi: 10.1175/2009bams2755.1

Leichenko, R.M., & O'Brien, K.L. (2008). *Environmental change and globalization: double exposures*. Oxford: Oxford University Press.

Leichenko, R. & Silva, J. A. (2014). Climate change and poverty: vulnerability, impacts, and alleviation strategies *WIREs Climate Change* 2014,3:213–232. doi: 10.1002/wcc.287.

Li, Y. & Wei, W.H.D. (2010). The spatial-temporal hierarchy of regional inequality of China. *Applied Geography*, 30, 303-316.

Liao, F.H.F. & Wei, Y.D. (2012). Dynamics, space, and regional inequality in provincial China: A case study of Guangdong province. *Applied Geography*, 35, 71-83.

Macauhub. (2008). Mozambique: 2008 cashew harvest may exceed 85,000 tonnes. Retrieved at: http://www.macauhub.com.mo/en/2008/04/08/4840/

Mather, D., Cunguara, B., & Boughton, D. (2008). *Household income and assets in rural Mozambique, 2002-2005: Can pro-poor growth be sustained?* DE/MINAG Working Paper #66E, Maputo.

Matyas, C.J., & Silva, J.A. (2013). Extreme weather and economic well-being in rural Mozambique. *Natural Hazards*, 66, 31-49.

MINAG. (2005). *Trabalho de Inquérito Agrícola* 2005. Ministério da Agricultura e Desenvolvimento Rural, Maputo: Mozambique.

MINAG. (2008). *Trabalho de Inquérito Agrícola 2008.* Ministério da Agricultura e Desenvolvimento Rural, Maputo: Mozambique.

MINAG. (2012). *Trabalho de Inquérito Agrícola 2012.* Ministério da Agricultura e Desenvolvimento Rural, Maputo: Mozambique.

Narayan, D., Patel, R., Schafft, K., Rademacher, A., & Koch-Shulte, S. (2000). *Voices of the poor: Can anyone hear us?* Oxford University Press and World Bank, New York, 360.

Nissanke, M., & Thorbecke, E. (2006). Channels and Policy Debate in the Globalization-Inequality-Poverty Nexus. *World Development*, 34, 1338–1360.

ReliefWeb. (2007). *FEWS Mozambique food security warning*. Retrieved at: http://reliefweb.int/report/mozambique/fews-mozambique-food-security-warning-cyclone-favio-drought-rack-south-north.

ReliefWeb. (2008a). *FEWS Mozambique Food Security Outlook Apr to Sep 2008.* Retrieved at: http://reliefweb.int/report/mozambique/fews-mozambique-food-security-outlook-apr-sep-2008.

ReliefWeb. (2008b). *Mozambique: emergency situation report, 04 Apr 2008*. Retrieved at: http://reliefweb.int/report/mozambique/mozambique-emergency-situation-report-04-apr-2008.

ReliefWeb. (2008c). *Mozambique: Floods and Cyclone "Jokwe" Situation Report No. 14*. Retrieved at: http://reliefweb.int/report/mozambique/mozambique-floods-and-cyclone-jokwe-situation-report-no-14.

ReliefWeb. (2008d). *Mozambique: Cyclone Jokwe DREF operation n° MDRMZ003 Final Report.* Retrieved at: http://reliefweb.int/report/mozambique/mozambique-cyclone-jokwe-dref-operation-n%C2%B0-mdrmz003-final-report

Rodima-Taylor, D. (2012). Social innovation and climate adaptation: Local collective action in diversifying Tanzania. *Applied Geography*, 33, 128-134.

Scheffran, J., Marmer, E., & Sow, P. (2012). Migration as a contribution to resilience and innovation in climate adaptation: Social networks and co-development in Northwest Africa. *Applied Geography*, 33, 119-127.

Sen, A. (1981). *Poverty and famines: An essay on entitlement and deprivation*. Clarendon Press, Oxford.
Sen A. (1999). *Development as freedom*. Oxford University Press, Oxford.
Silva, J.A. (2014). Relating local experiences to national shifts in rural income inequality in Mozambique. *Review of Regional Studies*, 34, 23-50.
Silva, J.A. & Matyas, C.J. (2014). Relating rainfall patterns to agricultural income: Implications for rural development in Mozambique. *Weather, Climate, and Society*, 6, 218-236. DOI: 10.1175/WCAS-D-13-00012.1.
Simler, K., & Nhate, V. (2005). *Poverty, inequality, and geographic targeting: Evidence from small-area estimates in Mozambique.* Food, Consumption, and Nutrition Division Discussion Paper No. 192. International Food Policy Research Institute, Washington D.C.
Stal, M. (2011). Flooding and relocation: The Zambezi River Valley in Mozambique. *International Migration* 49, e125-e145. doi:10.1111/j.1468-2435.2010.00667.x
Skoufias, E., Rabassa, M., & Olivieri, S. (2012). The forecast for poverty: a review of the evidence. In: Skoufias, E., ed. *The Poverty and Welfare Impacts of Climate Change: Quantifying the Effects, Identifying the Adaptation Strategies*. Washington DC: The World Bank, 17–54.
UNDP (2009). *Human Development Report 2009: Human Mobility: Overcoming barriers to development.* United Nations Development Programme: New York. http://hdr.undp.org/sites/default/files/reports/268/hdr_20072008_en_complete.pdf Retrieved at: http://hdr.undp.org/sites/default/files/reports/269/hdr_2009_en_complete.pdf
USAID. (2007). Mozambique - Floods and Cyclone Fact Sheet #1, Fiscal Year (FY) 2007. http://reliefweb.int/sites/reliefweb.int/files/resources/A0E530C50EF85F7FC12572A6007CC07A-Full_Report.pdf. Accessed 06 August 2014
USAID. (2008). Mozambique food security update. http://www.fews.net/sites/default/files/documents/reports/Mozambique_2008_04%20%20final.pdf. Accessed 06 August, 2014.
World Bank (2014). *World Bank Open Data*. Retrieved at: http://data.worldbank.org/indicator/NY.GDP.PCAP.CD?page=1
World Bank. (2006). *World Development Report 2006: Equity and development*. Washington, D.C.: World Bank.
Zhang, X. & Kanbur, R. (2001). What difference do polarization measures make? An application to China. *Journal of Development Studies*, 37, 85-98.

Table 1 Income and Poverty Profile for Weather Groups

	Mean Household Income/AE		Minimum		Maximum		Median Household Income/AE		Poverty Headcount[b]		Poverty Gap		Number of Observations	
	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008	2005	2008
Group_1: Cabo Delgado and Nampula	2,932	2,441*	41	60	29,661	29,146	1,825	1,274	85%	87%*	54%	63%	328	283
	216	*237*							*0.02*	*0.02*	*0.02*	*0.02*		
Group_2: High Altitude Niassa, Nampula, Tete, Zambezia	2,492	2,499	0	0	143,410	35,965	1,238	1,420	87%	85%*	62%	59%	1,130	882
	134	*109*							*0.01*	*0.02*	*0.01*	*0.01*		
Group_3: TCs Jaya/Jokwe	3,064	1,813*	0	0	74,336	14,518	1,354	1,049	86%	92%*	60%	69%	261	194
	419	*178*							*0.02*	*0.03*	*0.02*	*0.03*		
Group_4: Zambezia Valley, Manica, Sofala	3,126	3,038	1	0	138,386	671,568	1,570	1,630	84%	82%*	56%	56%	516	372
	316	*376*							*0.02*	*0.02*	*0.02*	*0.02*		
Group_5: TC Favio	4,523	3,621**	0	0	48,557	37,920	2,653	2,061	71%	80%*	44%	52%	284	240
	349	*334*							*0.03*	*0.03*	*0.02*	*0.03*		
Group_6: Inhambane, mostly coastal	4,754	5,723	37	11	50,263	48,763	2,324	2,614	70%	71%*	43%	41%	228	157
	450	*724*							*0.03*	*0.04*	*0.03*	*0.03*		
Group_7: Gaza, some inland Inhambane	4,637	4,158	0	1	125,250	76,984	2,467	2,000	75%	77%*	45%	49%	330	206
	501	*527*							*0.03*	*0.04*	*0.03*	*0.03*		
Group_8: Maputo Province	8,830	8,680**	1	0	289,816	255,697	3,934	3,369	60%	58%*	35%	39%	236	265
	1,601	*1,331*							*0.04*	*0.04*	*0.03*	*0.03*		

Source: Authors' calculations using TIA 2005/2008 household survey data.

[a] Values reported in Mozambican New Meticais at constant 2005 values. All variables population weighted.

[b] Poverty figures calculated using $1.25 USD poverty line.

Standard errors reported in italics.

*= p < 01 and ** = p < .1; significance level for t-tests (using natural logs of mean income values to better approximate a normal distribution) and Chi Square tests for poverty headcount.

Table 2 Gini Index Decomposition for Total Household Income/AE by Weather Groups, 2005

Weather Group & Geographic Region	Gini Index Coefficient	Population Share	Income Share	Absolute Contribution to Within-Group Inequality	Relative Contribution to Within-Group Inequality
Group_1: Cabo Delgado and Nampula	0.529	12.5%	11.2%	0.007	1.2%
	0.02	*0.01*	*0.01*	*0.001*	*0.00*
Group_2: High Altitude Niassa, Nampula, Tete, Zambezia	0.595	36.9%	27.9%	0.061	10.0%
	0.01	*0.01*	*0.02*	*0.005*	*0.01*
Group_3: TCs Jaya & Jokwe	0.640	13.9%	12.9%	0.011	1.9%
	0.04	*0.01*	*0.02*	*0.002*	*0.00*
Group_4: Zambezia Valley, Manica, Sofala	0.611	13.6%	12.9%	0.010	1.7%
	0.03	*0.01*	*0.01*	*0.002*	*0.00*
Group_5: TC Favio	0.572	7.2%	9.8%	0.004	0.7%
	0.02	*0.05*	*0.01*	*0.001*	*0.00*
Group_6: Inhambane, mostly coastal	0.587	6.6%	9.6%	0.004	0.6%
	0.03	*0.01*	*0.01*	*0.001*	*0.00*
Group_7: Gaza, some inland Inhambane	0.613	7.2%	10.1%	0.005	0.7%
	0.04	*0.01*	*0.01*	*0.001*	*0.00*
Group_8: Maputo Province	0.697	2.2%	5.8%	0.001	0.1%
	0.05	*0.00*	*0.01*	*0.000*	*0.00*
Within-Group Inequality for Sample	.	.	.	0.104	16.9%
Between-Group Inequality for Sample	.	.	.	0.154	25.1%
Overlap Inequality for Sample	.	.	.	0.357	58%
Full Sample	0.615	100%	100%	0.615	100%

Source: Authors' estimates using the 2005 TIA Household Survey Data.

Standard errors are in italics.

Table 3 Gini Index Decomposition for Total Household Income/AE by Weather Groups, 2008

Weather Group & Geographic Region	Gini Index Coefficient	Population Share	Income Share	Absolute Contribution to Within-Group Inequality	Relative Contribution to Within-Group Inequality
Group_1: Cabo Delgado and Nampula	0.585	12.7%	10.1%	0.008	1.2%
	0.03	*0.01*	*0.01*	*0.00*	*0.00*
Group_2: High Altitude Niassa, Nampula, Tete, Zambezia	0.549	39.6%	32.1%	0.070	11.4%
	0.01	*0.01*	*0.02*	*0.01*	*0.01*
Group_3: TCs Jaya & Jokwe	0.564	12.2%	7.2%	0.005	0.8%
	0.03	*0.01*	*0.01*	*0.00*	*0.00*
Group_4: Zambezia Valley, Manica, Sofala	0.588	12.9%	12.8%	0.010	1.6%
	0.02	*0.01*	*0.01*	*0.00*	*0.00*
Group_5: TC Favio	0.604	7.0%	8.3%	0.004	0.6%
	0.03	*0.01*	*0.01*	*0.00*	*0.00*
Group_6: Inhambane, mostly coastal	0.618	6.0%	11.2%	0.004	0.7%
	0.04	*0.01*	*0.02*	*0.00*	*0.00*
Group_7: Gaza, some inland Inhambane	0.621	5.6%	7.5%	0.003	0.4%
	0.04	*0.01*	*0.01*	*0.00*	*0.00*
Group_8: Maputo Province	0.692	3.9%	10.9%	0.003	0.5%
	0.04	*0.00*	*0.02*	*0.00*	*0.00*
Within-Group Inequality for Sample	.	.	.	0.105	17.2%
Between-Group Inequality for Sample	.	.	.	0.202	32.9%
Overlap Inequality for Sample	.	.	.	0.305	49.9%
Full Sample	0.613	100%	100%	0.613	100%

Source: Authors' estimates using the 2008 TIA Household Survey Data.

Standard errors are in italics.

Table 4 Decomposition of the Polarization Index (DER) for Total Household Income/AE by Weather Groups, 2005 (α = 0.75*)

Weather Group & Geographic Region	DER Index Coefficient	Deficit Component (D)	Surplus Component (S)	D/S Ratio	Absolute Contri-bution to Within-Group Polariza-tion	Relative Contri-bution to Within-Group Polariza-tion
Group_1: Cabo Delgado and Nampula	0.253	0.030	0.007	4.38	0.004	1.2%
Group_2: High Altitude Niassa, Nampula, Tete, Zambezia	0.306	0.109	0.017	6.57	0.035	11.2%
Group_3: TCs Jaya & Jokwe	0.372	0.040	0.007	5.87	0.006	2.0%
Group_4: Zambezia Valley, Manica, Sofala	0.337	0.037	0.007	5.39	0.006	1.8%
Group_5: TC Favio	0.266	0.014	0.005	3.11	0.002	0.6%
Group_6: Inhambane, mostly coastal	0.286	0.013	0.004	3.11	0.002	0.5%
Group_7: Gaza, some inland Inhambane	0.368	0.015	0.005	3.30	0.002	0.6%
Group_8: Maputo Province	0.524	0.004	0.001	2.40	0.000	0.1%
Within-Group Polarization for Sample	.	.	.	.	0.056	17.9%
Between-Group Polarization for Sample*	.	.	.	.	0.257	82.1%
Full Sample	0.314	0.262	0.052	5.04	0.314	100%

Source: Authors' estimates using the 2005 TIA Household Survey Data.

*Pure between-group polarization index : 0.0397

Table 5 Decomposition of the Polarization Index (DER) for Total Household Income/AE by Weather Groups, 2008 (α = 0.75*)

Weather Group & Geographic Region	DER Index Coefficient	Deficit Component (D)	Surplus Component (S)	D/S Ratio	Absolute Contri-bution to Within-Group Polari-zation	Relative Contri-bution to Within-Group Polari-zation
Group_1: Cabo Delgado and Nampula	0.283	0.037	0.006	6.03	0.004	1.3%
Group_2: High Altitude Niassa, Nampula, Tete, Zambezia	0.255	0.106	0.020	5.24	0.035	12.5%
Group_3: TCs Jaya & Jokwe	0.277	0.040	0.005	8.22	0.006	1.0%
Group_4: Zambezia Valley, Manica, Sofala	0.328	0.032	0.007	4.68	0.006	1.6%
Group_5: TC Favio	0.288	0.017	0.004	4.01	0.002	0.5%
Group_6: Inhambane, mostly coastal	0.302	0.011	0.005	2.31	0.002	0.5%
Group_7: Gaza, some inland Inhambane	0.286	0.012	0.003	3.71	0.002	0.4%
Group_8: Maputo Province	0.661	0.006	0.003	2.47	0.000	0.3%
Within-Group Polarization for Full Sample	.	.	.	.	0.057	18.9%
Between-Group Polarization for Full Sample*	.	.	.	.	0.257	81.2%
Full Sample	0.314	0.261	0.053	4.79	0.314	100%

Source: Authors' estimates using the 2008 TIA Household Survey Data.

*Pure between-group polarization index : 0.047

Table 6 Variation in Inequality and Polarization for Weather Groups

Weather Group & Region	Gini Index Rank		DER Index Rank		D/S Ratio Rank[a]		% Δ Gini Coeff.	% Δ DER Coeff.	% Δ D/S Ratio[b]
	2005	2008	2005	2008	2005	2008	2005-2008	2005-2008	2005-2008
Group_1: Cabo Delgado and Nampula	8	6	8	6	5	7	11%	12%	38%
Group_2: High Altitude Niassa, Nampula, Tete, Zambezia	5	8	4	8	8	6	-8%	-17%	-20%
Group_3: TCs Jaya & Jokwe	2	7	2	7	7	8	-12%	-26%	40%
Group_4: Zambezia Valley, Manica, Sofala	4	5	3	2	6	5	-4%	-3%	-13%
Group_5: TC Favio	7	4	6	4	2	4	6%	8%	29%
Group_6: Inhambane, mostly coastal	6	3	5	3	3	1	5%	6%	-26%
Group_7: Gaza, some inland Inhambane	3	2	7	5	4	3	1%	8%	12%
Group_8: Maputo Province	1	1	1	1	1	2	-1%	26%	3%

Source: Authors' estimates using the 2005 and 2008 TIA Household Survey Data.

[a] Lower D/S ranking denotes smaller proportion of lower income households.

[b] Positive change in D/S ratio indicates downward shift along the income distribution. The inverse is true for negative change.