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Climate volatility deepens poverty vulnerability in developing countries

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Abstract
Extreme climate events could influence poverty by affecting agricultural productivity and raising prices of staple foods that are important to poor households in developing countries. With the frequency and intensity of extreme climate events predicted to change in the future, informed policy design and analysis requires an understanding of which countries and groups are going to be most vulnerable to increasing poverty. Using a novel economic-climate analysis framework, we assess the poverty impacts of climate volatility for seven socio-economic groups in 16 developing countries. We find that extremes under present climate volatility increase poverty across our developing country sample—particularly in Bangladesh, Mexico, Indonesia, and Africa—with urban wage earners the most vulnerable group. We also find that global warming exacerbates poverty vulnerability in many nations.

Keywords: climate extremes, volatility, poverty vulnerability, food prices

1. Introduction

Staple grains such as rice represent a significant source of expenditure, calories and earnings for many of the poor in developing countries (Cranfield *et al* 2003, Thurlow and Wobst 2003, Ulimengu *et al* 2009). This dependence has raised concern about how recent increases in food prices might affect poverty (IFPRI 2008). While the impacts of high food prices vary across different socio-economic groups in developing countries, analyses of survey data indicate that the short-run effect of the 2005–2007 staple food price increase was to worsen poverty for the majority of the poor (Ivanic and Martin 2008). Estimates from the Food and Agriculture Organization (FAO) indicate that rising prices were responsible for an increase in the proportion of hungry people in the developing world by about 75 million people between 2003–2005 and 2007 (FAO 2008).

The poverty vulnerability of developing countries to rising food prices motivates a need for better understanding of the drivers of commodity price volatility and their linkages to poverty. One important source of volatility is adverse climate events, including extreme heat, droughts and floods. Although it is known that these events can detrimentally affect agricultural systems and food security (White *et al* 2006, Funk *et al* 2008, Lobell *et al* 2008, Battisti and Naylor 2009), the impact of climate volatility on national-scale poverty has not yet been quantified, nor has the impact on the poor in different socio-economic strata. In addition, climate studies consistently show that further increases in GHG concentrations are likely to cause increases in hot, wet and dry extremes (e.g., Diffenbaugh *et al* 2005, 2007, IPCC 2007), and there is evidence that such changes to climate volatility are already occurring (Easterling *et al* 2000, IPCC 2007). As the frequency and intensity of climate extremes increase, crop production damages from such events will change (Schmidhuber and Tubiello 2007, Naylor *et al* 2007). Sharp reductions in crop supply put upward pressure on food prices, thereby having a significant poverty impact. Therefore, in order to create informed policy responses to the threat of increased poverty vulnerability as well as to better quantify potential damages associated with varying greenhouse targets, it is imperative to understand the linkages between developing country poverty and climate extremes.

However, analyses combining both rigorous climate science and economic theory have been notably lacking to date. This paper provides an integrated analytical framework with empirical and theoretical foundations that can be used to study the social dimensions of extreme events, future volatility, and other potential climate effects. It then examines which socio-economic groups and countries are most vulnerable to climate extremes, providing a basis for climate adaptation and poverty reduction strategies in the developing world.

2. Climate extremes in current and future A2 scenario

We seek to quantify the vulnerability of the poor to potential changes in climate volatility, in the context of the frequency and magnitude of annual-scale hot, dry, and wet extremes. We draw on the unprecedented global climate model database that has been assembled as part of the 'CMIP3' project and heavily used in the IPCC Fourth Assessment Report (IPCC 2007), to consider three distinct agricultural productivity stressors. These annual-scale extreme climate indices from Frich *et al* (2002) are available in the CMIP3 multi-model archive: (1) the per cent of annual total precipitation due to events exceeding the 1961–1990 95th percentile; (2) the maximum number of consecutive dry days; and (3) the heat wave duration index (the maximum period greater than 5 days with the daily maximum temperature greater than the 1961–1990 normal). We thus quantify the response of the 30-year-maximum values of wet, dry, and hot extremes.

We analyze 30 year periods from 1971 to 2000 in the 20th century simulations and 2071 to 2100 in the simulations under the IPCC's A2 scenario, examining output from 'run 1' of the seven models that have archived the extreme climate indices. Within each time period and scenario, and at the 108 Agro-Ecological Zone (AEZ) level of spatial disaggregation, we calculate the extreme climate indices: (1) the 30-year-maximum value in the 20th century period; (2) the 30-year-maximum value in the 21th century period; and (3) the number of years in the 21st century period that exceeded the 30-year-maximum value of the 20th century period. For each variable, we interpolate the data from each GCM to a common 1° geographical grid, and calculate the maximum annual value of the variable in the 1971–2000 and 2071–2100 time-series of each GCM at each grid point. We then determine the number of years whose value exceeded that maximum annual value in each of the time-series at each grid point: 1971–2000 and 2071–2100 in the A2 scenario. We compute the mean value at each grid point across the seven GCMs, as well as the inter-model standard deviation of the 21st century minus 20th century fractional difference.

We next interpolate these GCM occurrence data from the common 1° grid to the 0.5° geographical grid upon which the AEZ data is based, select the grid points corresponding to each of the focus countries, and compute the area-weighted mean occurrence in each time period/scenario for each AEZ in a given country and for the country as a whole. We also calculate the area-weighted mean of the values of the respective grid points falling within the borders of each country.

The CMIP3 ensemble exhibits substantial changes in extreme climate in the late 21st century of the A2 scenario (figure 1). The occurrence of what is now the 30-year-maximum extreme wet event increases (A2 minus present, relative to present) throughout the world, with maximum increases of greater than 900% occurring over Southeast Asia. The absolute magnitude of the 30-year-maximum event is also greater throughout the world in the A2 scenario than at present, with peak increases of greater than 40% also in Southeast Asia. All countries exhibit substantial increases in the occurrence and magnitude of extreme hot events, with the occurrence of the present 30-year-maximum event increasing more than 2700% in parts of the northern Mediterranean, and the magnitude of the 30-year-maximum event increasing 1000% to more than 2250% in much of central Africa. Most countries also display increases in the occurrence and magnitude of extreme dry events, with peak changes of greater than 800% and 60% (respectively) occurring over Mediterranean Europe. A handful of countries display decreases in occurrence, magnitude, or both of extreme dry events. Countries where the intensity and frequency of extreme consecutive dry days decline include Colombia and Uganda, while Tanzania, Indonesia, and the Philippines experience less intense but more frequent years of such extreme climate. The change in the magnitude of the extreme hot and wet events is reduced in the B1 scenario relative to the A2 scenario for all focus countries (table 1). This reduction in the severity of change in the B1 scenario is less universal for the magnitude of the extreme dry event.

3. Economic data and methods

The magnitude and spatial heterogeneity of changes in climate volatility suggest that the impacts on poverty could also be large and heterogeneous. To quantify the vulnerability of developing countries to being impoverished by current climate volatility we focus on the response to once-in-30-year-climate events. For the staple grains sector, climate outcomes for a given country in a given year can be interpreted as exogenous supply-side shocks to sector productivity. Controlling for trends, climate outcomes affecting grains production can thus be considered draws from a probability distribution of interannual grains productivity changes. We generate such productivity change distributions for 16 developing countries (sample selection discussed below) by implementing zero-mean normal distributions characterized by standard deviations of interannual staple grains productivity changes estimated from historical data. These estimates are taken from Valenzuela (2009) or are estimated from FAOSTAT data (FAO 2009). For each country in our sample of 16 'focus' countries, the productivity change that corresponds to a once-in-30-year-climate extreme is determined to be the interannual productivity change that occurs 3.33% of the time. However, since we are drawing directly from statistically estimated distributions of interannual productivity changes, the once-in-30-year agricultural productivity change for a given country is

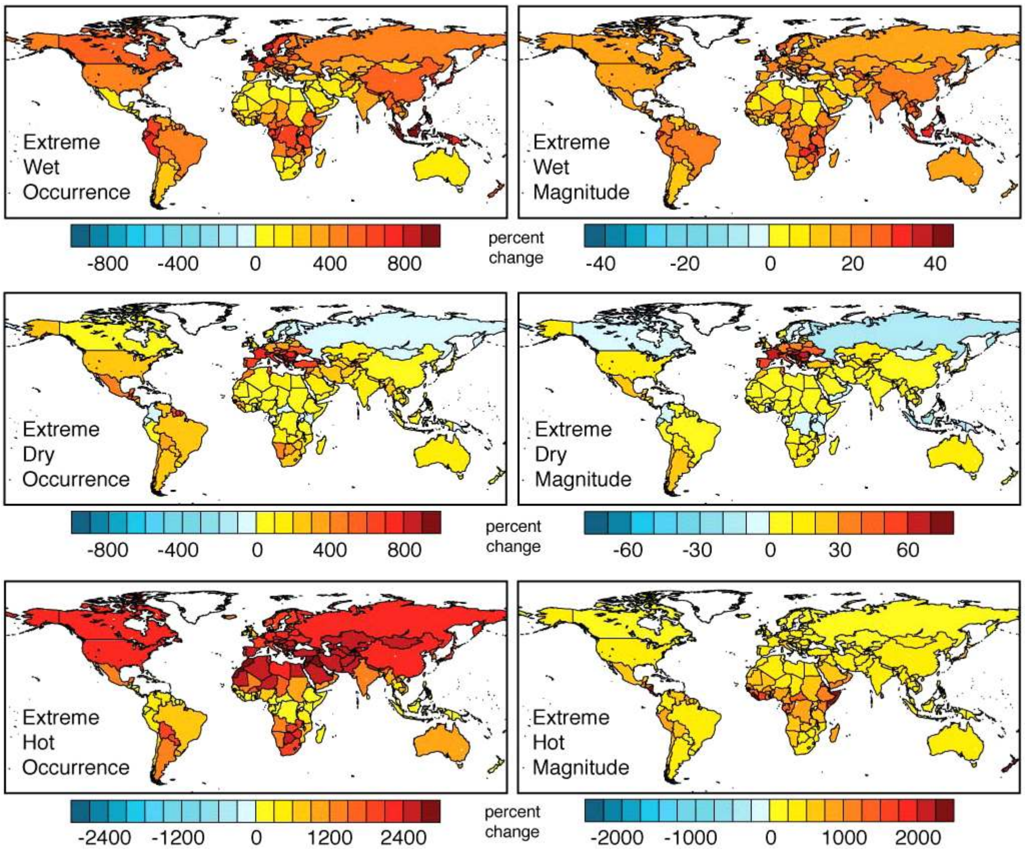

Figure 1. Changes in frequency and magnitude of climate extremes. Percentage changes are calculated as ((A2 minus current)/current) × 100%. The current and A2 periods cover 1971–2000 and 2071–2100 in the CMIP3 ensemble, respectively.

distinct from the once-in-30-year changes for other countries, and cannot be directly mapped to the historically observed maximum values of the annual-scale extreme climate indices (figure 1, table 1).

We examine the poverty impacts of the current climate's once-in-30-year productivity shocks using a modified version of the comparative static computable general equilibrium (CGE) simulation model GTAP (Hertel 1997). The model uses the empirically robust assumptions of constant returns to scale and perfect competition, and is modified to better delineate distributional impacts. We introduce factor market segmentation which is important in countries where the rural sector remains a dominant source of poverty (Keeney and Hertel 2005), and disaggregate land endowments by AEZ (Hertel *et al* 2009b). The model is supported by Version 6 of the GTAP Database (Dimaranan 2006) and the GTAP Land Use Database (Lee *et al* 2009, Monfreda *et al* 2009). The combined database represents the 2001 global economy, and the climate extreme simulations thus represent differences from this benchmark.

Poverty analysis is facilitated by a special poverty module which has been added to GTAP following the approach of Hertel *et al* (2009a). Implementation of this module requires comprehensive processing of a national household survey and this is the limiting factor constraining the size of our sample of focus countries which comprises 16 countries in Africa, Asia and Latin America (table 1)[6]. While this is not a random sample of countries, it does encompass a wide range of developing countries with greatly differing patterns of poverty. Within each country, poverty is broken down into socio-economic strata based on primary source of income (95% or more of income from the following sources): agricultural self-employed (farm income), non-agricultural (non-agricultural self-employment earnings), urban labor (urban household, wage labor income), rural labor (rural household, wage labor income), transfer payment dependent, urban diverse, and rural diverse (Hertel *et al* 2004).

The poverty module utilizes a micro-simulation for representative households at the poverty line in each socio-economic stratum to determine changes in poverty headcount based on changes in real income. We use the World Bank's \$1/day Purchasing Power Parity definition of poverty to ensure comparability across countries (Chen and Ravallion 2001)[7]. Each household maximizes its utility obtained from an econometrically estimated AIDADS demand system (Rimmer and Powell 1996, Cranfield *et al* 2003). This yields a new preferred consumption bundle and a new level of utility in the

[6] The data for Tanzania are from the National Bureau of Statistics (2002) and were processed by Ana Rios (Inter-American Development Bank). The data for the remaining 15 focus countries were processed by Ivanic (World Bank), and documented in Hertel *et al* (2004) and Hertel *et al* (2009a).

[7] This is more stringent than the more recently estimated \$1.25/day poverty line (Ravallion *et al* 2008).

Table 1. Simulated extreme climate indicators for the 16 focus countries. The 20C columns show the mean of the GCM values of the respective extreme climate metrics for the late 20th century period (1971–2000). The B1 columns show the mean of the GCM values of the respective extreme climate metrics for the late 21st century period (2071–2100) in the IPCC SRES B1 scenario, which falls at the low greenhouse gas end of the IPCC illustrative scenario suite (Meehl *et al* 2007). The A2 columns show the mean of the GCM values of the respective extreme climate metrics for the late 21st century period (2071–2100) in the IPCC SRES A2 scenario, which falls at the high greenhouse gas end of the IPCC illustrative scenario suite. The A2v columns show the inter-model standard deviation of the GCMs.

	Number of average consecutive dry days				Per cent of annual total precipitation due to events exceeding 1961–1990 95th percentile				Maximum period greater than 5 days with the daily maximum temperature greater than the 1961–1990 normal			
	20th century	B1	A2	A2v	20th century	B1	A2	A2v	20th century	B1	A2	A2v
Bangladesh	94.4	105.6	109.9	27.6	32.1	36.0	41.7	12.4	20.8	60.7	101.3	59.7
Brazil	142.4	149.8	153.6	53.8	30.4	34.5	37.3	9.3	27.4	70.0	135.3	85.9
Chile	70.5	78.5	88.1	35.0	30.4	32.6	34.3	6.7	9.3	28.2	67.7	42.5
Colombia	76.5	72.2	71.4	36.3	27.4	30.0	34.1	8.9	19.3	39.2	104.0	71.9
Indonesia	51.3	45.0	45.5	31.3	27.2	31.5	36.2	9.2	9.8	13.4	31.1	32.8
Mexico	143.2	145.5	146.9	52.7	33.5	36.7	41.7	8.9	21.3	54.3	108.8	65.1
Mozambique	96.6	110.6	119.6	41.8	36.5	39.1	42.1	10.9	21.3	66.6	145.0	93.7
Malawi	103.6	110.8	115.2	42.9	37.7	41.6	47.5	10.0	19.8	52.7	98.1	62.3
Peru	94.1	96.1	95.3	35.6	26.2	30.3	32.3	7.0	12.8	36.3	118.1	80.7
Philippines	59.5	60.4	57.8	39.3	27.4	33.6	36.0	7.6	11.4	22.5	50.2	53.6
Thailand	96.3	102.3	105.9	26.0	32.2	37.8	41.0	9.6	26.0	50.7	97.6	57.9
Tanzania	131.8	135.8	131.5	43.9	29.4	33.6	37.5	5.5	11.6	34.0	86.2	60.1
Uganda	71.2	69.5	66.1	34.9	27.9	30.6	34.0	6.0	10.9	30.4	81.4	63.9
Venezuela	124.3	132.5	134.5	41.0	29.9	32.0	33.1	6.7	18.5	66.6	153.8	95.4
Vietnam	79.6	78.2	82.8	26.5	30.9	34.6	38.5	8.6	23.3	44.3	79.6	47.0
Zambia	174.3	181.5	179.8	46.6	26.5	32.9	35.1	7.1	22.1	60.2	139.6	75.6
Average	100.6	104.6	106.5	38.4	30.4	34.2	37.7	8.4	17.8	45.6	99.9	65.5

wake of any change in goods prices and factor incomes. The AIDADS demand system is well suited for poverty analysis, due to ability to characterize consumer behavior at low income levels. In particular, for each commodity, AIDADS provides estimates of subsistence quantities of consumption, as well as the propensity of households at the subsistence level to spend additional income on various goods and services. These two parameters, operating in conjunction with changes in per capita income, determine household expenditure shares at the poverty level of utility, which is the focal point of our analysis. Across the 16 country sample, the share of total expenditure devoted to food ranges from 41% in Brazil to 67% in Uganda so that any rise in food prices will have a sharp impact on real income, and hence poverty.

The poverty consequences of an adverse climate shock are evidenced through two channels: changes in earnings and changes in the real cost of living at the poverty line. The impact of a food price rise on earnings depends on the income sources for a given household group; these earnings shares are estimated for households in the neighborhood of the poverty line from household survey data. If earnings rise faster than the cost of living for households at the poverty line in a given stratum, then the poverty headcount will fall and vice versa. The responsiveness of the stratum poverty headcount to a given real income shock is determined by the density of the stratum population in the neighborhood of the poverty line and is also estimated from the household survey data. When combined with information about the distribution of national poverty across socio-economic strata, we are able to estimate the change in national poverty headcount.

Figure 2 reports the proportions of focus countries' total 2001 populations that are impoverished, grouping them into the seven strata that reflect the pattern of household earnings specialization. The darker shaded areas in each bar correspond to the agriculture and rural households in our sample. It can be seen that these dominate the poverty picture in nearly every country. Bangladesh, Mozambique, Malawi, Tanzania, Uganda, and Zambia stand out as already experiencing particularly high incidences of poverty. However, given that Bangladesh's total population is more than that of the combined population of all five African countries, the absolute number of Bangladeshi poor is greater.

4. Poverty changes due to climate extremes

Using the framework just described, we simulate once-in-30-year-climate extremes one country at a time, and generate economic changes that are attributable only to the extreme climate impacts in that country. We thereby mitigate the effects of international price transmission that may have arisen due to agricultural productivity volatility in other countries (Valenzuela *et al* 2007). We can thus be confident that the resulting poverty changes are attributable to grains price and supply effects arising due to extreme climate outcomes in those countries alone. These poverty changes are indicated by the cross-hatched areas for each focus country in figure 2.

The countries with the highest shares of populations entering poverty in the wake of these extreme events include Bangladesh, Mexico, Mozambique, Malawi, Tanzania, and Zambia (figure 2). In Malawi and Zambia, simulated

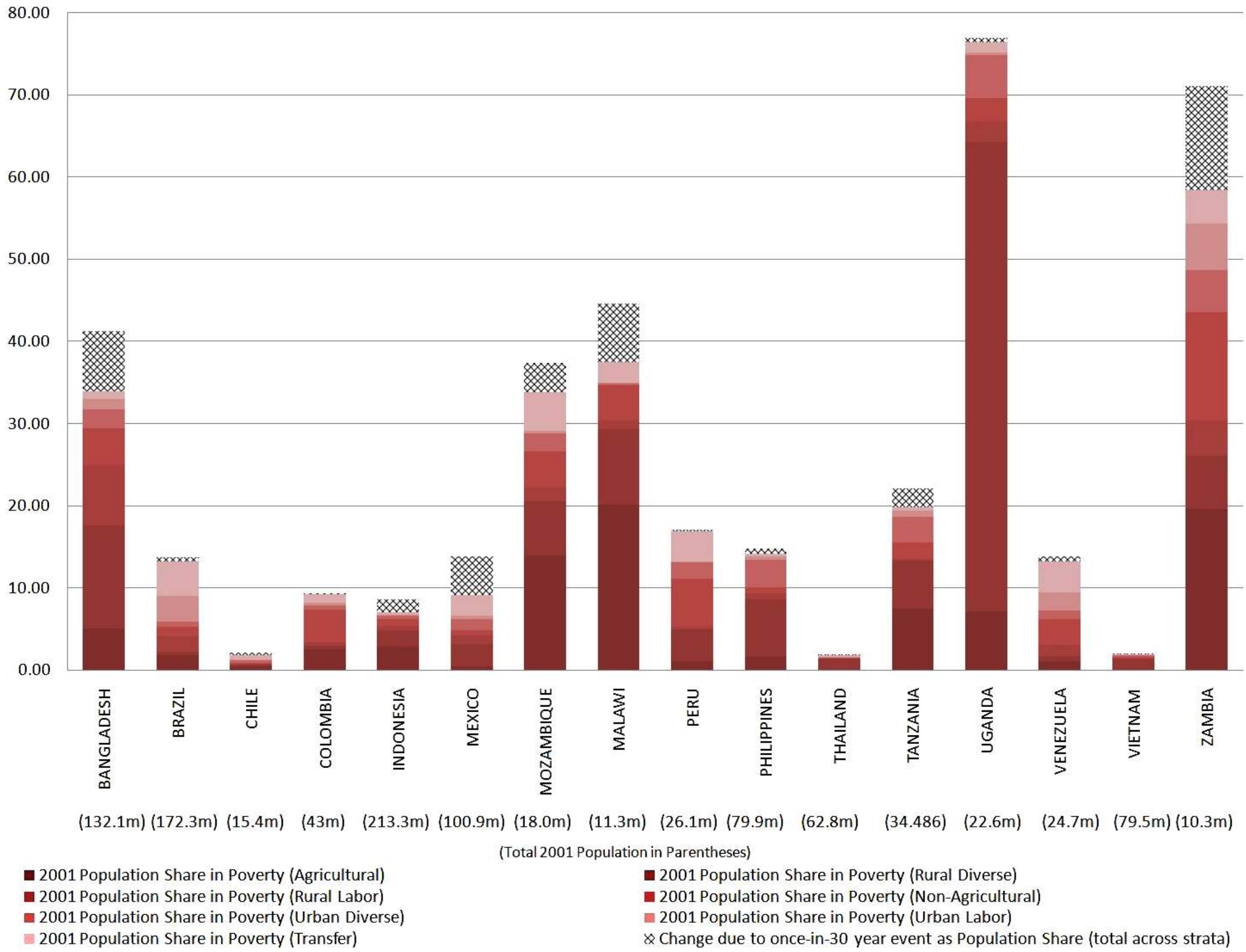

Figure 2. Poverty in sample countries in 2001 and change in poverty due to extreme climate, as shares of 2001 populations.

grains productivity declines of about 75% cause the poverty headcount in those countries to increase by about seven percentage points relative to their total populations. The large magnitudes of the declines in grains productivity are not unrealistic, and are reflected in the historically observed interannual changes in grains production. Grains productivity in Malawi and Zambia declined by between 50 and 59% in the period 1991–1992, respectively, when southern Africa experienced a severe ENSO-related drought (Glantz *et al* 1997). Cereal consumption—measured as daily calories consumed per person from cereal—declined by 8.8% in Malawi and by 1.3% in Zambia during this period (FAO 2009).

A closer look at the poverty distribution by stratum in each country from figure 2 can foreshadow where the impacts of an extreme climate year will be felt most sharply. Table 2 reports the percentage changes in poverty due to climate extremes by socio-economic stratum and country. These results indicate tremendous heterogeneity in the poverty vulnerability to climate extremes across different segments of the population—when differentiated by primary income source (stratum). The bottom row in table 2 reports the simple average of percentage changes across countries, for a given stratum. From this, we can see that the most vulnerable group is the urban, wage-labor-dependent stratum. While the urban labor group contributes modestly to total poverty in this sample of countries (figure 2), it appears to be highly vulnerable to extreme climate events. Indeed, the poverty rate for this group doubles in Malawi under the once-in-30-year-climate event (table 2). Zambia and Mexico also show high vulnerability among this group. The source of the vulnerability of the urban poor is their extreme exposure to food price increases. Since food is a major expenditure, this group's overall consumption falls with rising prices, pushing them below the poverty threshold of consumption.

Agricultural households, on the other hand, are much less exposed (an average 9.2% poverty change under extreme events—table 2). This group is generally hurt by the adverse productivity shock from a food consumption perspective. However, they are partially insulated from the effects of the higher prices since they also benefit (on the income side) as producers of food. The other groups tend to fall in between these two extremes. Rural (and, to a lesser extent, urban) diversified households tend to earn a significant portion of their income in agriculture, and therefore benefit from higher prices. Non-agricultural self-employed households are also somewhat

Table 2. Per cent change in poverty due to once-in-30-year-climate extreme by stratum and country.

	Socio-economic strata						
	Agricultural	Non-agricultural	Urban labor	Rural labor	Transfer	Urban diverse	Rural diverse
Bangladesh	***32.1***	***37.8***	***30.7***	11.1	0.8	***29.5***	***17.2***
Brazil	0.1	4.1	5.5	6.2	1.0	9.6	7.0
Chile	7.7	13.8	12.7	9.5	14.7	12.6	14.9
Colombia	0.1	0.4	1.0	1.0	0.6	0.6	0.5
Indonesia	***29.5***	12.1	19.2	***23.9***	5.9	***17.9***	***19.0***
Mexico	***52.2***	***36.7***	***95.4***	***52.1***	***61.8***	***37.4***	***43.2***
Mozambique	4.3	***15.3***	***16.2***	12.4	7.2	***26.6***	***16.0***
Malawi	***15.8***	9.0	***110.5***	***91.0***	11.1	***30.8***	***23.0***
Peru	2.4	1.9	3.6	2.6	0.5	1.5	1.4
Philippines	−17.7	10.2	***32.3***	***25.9***	8.5	6.0	3.8
Thailand	4.9	5.8	7.1	5.8	6.4	5.6	5.8
Tanzania	7.2	11.0	14.9	5.3	6.6	***21.3***	11.9
Uganda	−0.1	1.6	***16.4***	2.9	0.1	1.0	0.6
Venezuela	4.0	5.1	12.1	10.1	0.0	7.2	6.6
Vietnam	5.1	7.0	0.0	0.0	3.9	6.3	6.4
Zambia	0.0	***17.7***	***102.0***	***32.5***	10.9	***41.1***	10.6
Average	9.2	11.8	30.0	18.3	8.8	16.0	11.7

Table 3. Changes in the grains production weighted national averages of extreme dry events and the additional shares of national populations impoverished by simulated future extreme dry event.

		Change in poverty impact of changing extreme dry event intensity (current climate minus 2071–2100 A2 climate)	
	Percentage change in average consecutive dry days in extreme climate year between current and future A2 scenario	Additional share of population impoverished (in percentage points)	Additional number of people impoverished (in millions)
Bangladesh	16.25	1.35	1.79
Brazil	9.55	0.07	0.11
Chile	14.48	0.06	0.01
Colombia	−7.89	−0.00	−0.00
Indonesia	−5.11	−0.11	−0.23
Mexico	26.45	1.76	1.78
Mozambique	10.50	0.42	0.07
Malawi	2.59	0.27	0.03
Peru	3.61	0.01	0.00
Philippines	−2.88	−0.04	−0.03
Thailand	10.28	0.01	0.01
Tanzania	−0.35	−0.01	−0.00
Uganda	−7.57	−0.06	−0.01
Venezuela	8.81	0.07	0.02
Vietnam	4.20	0.01	0.01
Zambia	3.72	4.64	0.48
Average	5.42	0.53	0.25

insulated from the adverse productivity shocks in agriculture[8]. Given that the shares of developing countries' populations living in rural areas are projected to decrease by more than one-third between 2010 and 2050 (United Nations 2007), climate extremes may have greater national-scale poverty impacts in the future because of higher population concentrations in the more sensitive urban strata.

Thus far we have assessed the relationship between current climate volatility and poverty via fluctuations in staple grains productivity. We now consider the impact of potential changes in climate volatility in the future. We can use the climate volatility metrics (table 1) as proxies for changes in future staple grain productivity under extreme events. To do so, we scale the current climate-related grains productivity decline under a 1-in-30 scenario by the simulated changes in intensity of a given type of climate extreme, thus obtaining an estimate of future adverse grains productivity shocks that can be used as input to the economic model.

Table 3 shows the response of national-level poverty when the current once-in-30-year productivity decline is adjusted based on changes to the intensity of the 30-year-maximum extreme dry events under the A2 scenario, determined as national averages weighted by the value of grains production by AEZ. Bangladesh, Mexico, and Zambia have the greatest

[8] The impact on transfer dependent households hinges on how we index such transfer payments. Here, we assume that they are adjusted according to a national price index, which serves to insulate them to some degree.

additional vulnerability, with an additional 1.4, 1.8, and 4.6% of their populations being impoverished by future extreme climate, respectively. While the pattern of the vulnerabilities across strata and countries do not change and all strata become more vulnerable, self-employed agricultural households will tend to see the smallest increase in their vulnerability, while urban wage earners will see the greatest[9].

5. Conclusion

Our novel, inter-disciplinary analysis of climate–agriculture–poverty interactions takes advantage of available data from the FAO and the CMIP3 multi-GCM ensemble experiment. However, it has some clear limitations. Individual extreme events like floods and tropical storms are captured only implicitly by our annual data. In addition, we have used the simulated climate changes as proxies for changes in agricultural productivity. A complete treatment will include explicit modeling of agricultural productivity in response to projected changes in climate volatility. Finally, our framework does not consider the impact of alternative sequences of climate shocks. Thus we are unable to analyze how the susceptibility of the poor to detrimental climate may change after experiencing an extreme climate event, a topic of concern to many policy analysts (Adger 1999). In addition, it is important to note that there is uncertainty in the exact trajectory of climate volatility in the future, because of uncertainty in the physics of the climate system (as evidenced by the spread in the GCM projections and the difference between different emissions scenarios) (table 1).

Analysis of the countries and socio-economic strata that are most vulnerable to impoverishment from short-run food price increases associated with climate extremes will allow for better-informed strategic mobilization of international development resources and climate policy instruments. We find that climate extremes exert substantial stress on low income populations, and that there is considerable international heterogeneity in the response of poverty to climate volatility. Further, we find that the urban, wage labor households are likely to be the most vulnerable to climate extremes. Attempts to quantify the true value of different mitigation policies must integrate such heterogeneity of impacts, and adaptation policies must not neglect the urban poor.

The largest climate-induced poverty responses in our sample occur in Africa, with agriculture in many sub-Saharan countries being particularly sensitive to climate. Investment adaptation responses, such as irrigation investment in Tanzania, would thus reduce the magnitude of the agricultural productivity decline due to climate extremes (such as drought), thereby buffering the impact of the climate event on poverty. However, as experiences from South Africa and Ethiopia (Bryan *et al* 2009) point out, even when farmers are aware of the need for adaptation, through options like different farming practices and irrigation, they may be constrained by institutional factors, like barriers to access to credit and information. This suggests that, in addition to investments in infrastructure, an enabling institutional environment is required to significantly ameliorate the impacts of extreme climate events.

[9] Unfortunately, this framework cannot be extended to simulate changes in intensity of extreme wet and hot climate events. If the productivity shocks were scaled to reflect the intensity changes of those climate indices, then the interannual change in grains productivity would exceed negative 100%, which is infeasible.

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