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Abstract

Climate change is associated with an increasing frequency of extreme weather events, which can severely reduce people's welfare, especially in the Global South. Here, we analyse the impacts of rainfall shocks – including lacking and excessive rains – on economic and social outcomes, using micro-level panel data from rural Ecuador. We employ high-resolution climate data and georeferenced household survey data covering 2013 to 2019 to examine how single and repeated rainfall shocks affect income, poverty, and income distribution. Panel data regression models with household fixed effects show that rainfall shocks reduce per capita income by 9% on average. The income losses are larger for poor than for non-poor households. Two consecutive rainfall shocks have stronger negative income effects, especially among the poor, who have limited resilience capacity and lack the resources to recover quickly. Our estimates suggest that a second rainfall shock reduces the income among the poor by more than 50%. Recurrent rainfall shocks also increase the poverty rate, the poverty gap, and poverty severity. These results highlight the need to consider social heterogeneity of climate change impacts in research and policymaking to understand and enhance people's climate resilience.

Keywords: rainfall shocks, income, poverty, agriculture, Ecuador

JEL Classification: D31, I32, Q54

1. Introduction

Climate change is increasing global land and sea surface temperatures and the frequency and severity of extreme weather events, such as heavy rains, floods, droughts, and heat waves (MAATE, 2022; Yesuph et al., 2023). These trends will likely intensify in the coming years and decades (Seneviratne et al., 2021). Low- and middle-income countries in tropical and subtropical regions are particularly affected (De Cian et al., 2016; Mendelsohn et al., 2006) and will also experience the largest damage due to their high reliance on agriculture and their lower adaptive capacities in comparison to high-income countries (Mendelsohn et al., 2006; Chuang, 2019). International attention is often paid to Africa and Asia, but many Latin American countries are also highly vulnerable and adversely affected by extreme weather events (Castellanos et al., 2022).

Weather extremes can negatively impact numerous economic activities. The most exposed are those related to agriculture, fisheries, and forestry because temperature and precipitation directly contribute to these production activities (Herrera et al., 2018). However, other sectors may be affected due to decreased labour productivity, deterioration of human health, increased unemployment, and destruction of infrastructure (Acevedo et al., 2020; Pleninger, 2022; Nguyen et al., 2020). Rural areas are more vulnerable than urban areas, not only because rural households tend to be more reliant on weather-sensitive sectors but also because they are often poorer and have less access to information, technology, infrastructure, financial intermediation, and social protection (Dasgupta et al., 2014; Lohmann & Lechtenfeld, 2015; Nguyen et al., 2020). In other words, climate change is a poverty amplifier: it increases the poverty headcount and makes poor people poorer, thus representing a significant obstacle to achieving the Sustainable Development Goal of poverty eradication (Hallegatte et al., 2016 & 2018; Hallegatte & Rozenberg, 2017; Winsemius et al., 2018).

Several studies examine the relationship between weather shocks and income or poverty. Mendelsohn et al. (2007) and Lokonon et al. (2015) point out that the income of rural and farm households is strongly affected by extreme weather events. Arouri et al. (2015) and Narloch (2016) find that severe rainfall and floods decrease per capita income and that poorer households are generally more vulnerable. In sub-Saharan Africa, heatwaves, floods, and droughts are associated with income losses and a rise in poverty (Amare & Balana, 2023; Azzarri & Signorelli, 2020; Baez et al., 2020; Salvucci & Santos, 2020). The loss in welfare pushes vulnerable households into short and long-term poverty traps, and poor families face stronger negative income effects than non-poor families (Bangalore et al., 2017; Boansi et al., 2021; Dasgupta, 2007).

However, most previous research focuses on the effects of a single weather shock or extreme event. Climate change manifests in an increase in the frequency of extreme events, which may create challenging cycles where people do not have enough time to recover before already facing the next shock. Such cycles would impede households' assets and human capital accumulation and aggravate the impacts of recurring shocks, especially among the most vulnerable population groups. For example, Pleninger (2022) finds that multiple natural disasters increase poverty more when they occur more frequently, as recurrent shocks do not allow for sufficient time to recover. Although few studies have analyzed the impact of multiple types of single shocks (such as earthquakes, severe storms, or fires), the literature on the effects of recurrent weather shocks on income distribution and poverty is very scarce. Also, most existing studies on the links between climate change and poverty relate to Africa and Asia or use global modelling approaches. Very little micro-level applied research focuses on Latin America (Castellanos et al., 2022; Cardoso Silva et al., 2024).

Here, we address these research gaps by analyzing the effects of recurrent rainfall shocks (including insufficient or excessive rain) during the same period across two consecutive years on household income and poverty in rural Ecuador. We consider up to two recurrent rainfall shocks. The study combines nationally representative and geo-referenced panel survey data with high-resolution climate data to evaluate the heterogeneous effects of rainfall shocks. We also estimate their effects on the poverty gap and poverty severity. Household-level data is crucial, as it captures income distribution effects that aggregate data often dissimulates, because of the poor's relatively small share of the total economy (Hallegatte et al., 2018).

The rest of this article is structured as follows. Section 2 presents the conceptual framework, discussing potential mechanisms of the effects of rainfall shocks on income and poverty, and why facing another recurrent shock could have greater consequences. Section 3 explains the data and econometric estimation approaches. Section 4 presents the results, whereas Section 5 discusses some broader implications and concludes.

2. Conceptual framework

A fundamental element of climate change is the increase in global temperatures and changes in rainfall patterns. These alterations raise sea levels, lead to glacier retreat, acidify the oceans, and increase the frequency and intensity of extreme weather events such as heavy rains or droughts (MAATE, 2022). In this study, we focus on the impacts of recurrent rainfall shocks, including too much rain as well as lack of rain, on household welfare in rural areas.

Climate change and weather shocks can affect households and their income through different mechanisms (Figure 1). Many rural households are involved in agriculture as farmers or laborers, and agricultural productivity has declined due to climate change (Cui & Tang, 2024), especially in tropical and subtropical regions. However, there are also other mechanisms through which adverse income effects can occur. According to the literature, extreme rainfall and droughts affect people mainly through five channels: food prices, labor productivity, health, and damage to infrastructure or assets (Hallegatte & Rozenberg, 2017).

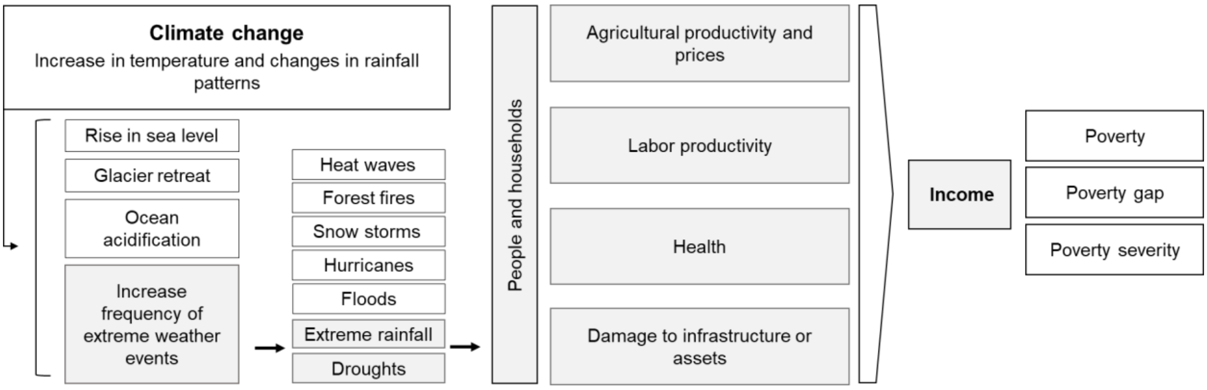


Figure 1: The link between climate change, income, and poverty

Changes in temperature, precipitation, and the frequency and severity of weather extremes result in lower agricultural productivity or sometimes complete crop losses (Cui & Tang, 2024). Reduced agricultural output contributes to food supply and demand imbalances, raising food prices (Rao et al., 2017). Rising food prices affect net food buying households negatively, reducing their real income. Food producers with net food selling positions may potentially benefit from rising prices. However, if the price effects do not offset the crop losses, income reductions are also likely for net food sellers (Olper et al., 2021; Nébié et al., 2021).

Extreme rains can cause flooding, which complicates access to workplaces, especially in rural areas where the transport infrastructure is often less developed. In order to deal with the consequences of flooding, more time and resources may be needed. Lower labor productivity and a potential decrease in work time due to extreme events will likely result in lower household incomes.

Another related mechanism is human health. Climate change and weather extremes can cause diseases or aggravate negative health conditions, mainly affecting poor people with low access to health services and who live in more hazard-exposed locations and conditions (Hales et al., 2014; Caminade et al., 2014). For instance, changes in temperature and rainfall patterns can increase exposure to infectious diseases, such as diarrhea, malaria, or dengue (Brouwer et al., 2007). In addition, lower access to food and essential nutrients weakens people's immune systems and makes them more vulnerable to disease. When household members fall sick, they might be unable to work and/or require special care, resulting in income losses (Hallegatte et al., 2018).

Finally, extreme weather events can directly cause loss of income and decrease employment opportunities by affecting the public infrastructure and the asset base of businesses and households (Carter et al., 2007; Rao et al., 2017; Winsemius et al., 2018).

Our study focuses on the net impact of rainfall shocks on rural household incomes related to these mechanisms and possibly others. We also evaluate the impact on income poverty, the poverty gap, and poverty severity. Based on the literature (Birkmann et al., 2022; Herrera et al., 2018; Günther & Harttgen, 2009; Islam & Winkel, 2017), we hypothesize that weather extremes, in general, and rainfall shocks, in particular, negatively affect the poorest population segments the most, thus increasing poverty and inequality. We also posit that repeated rainfall shocks have more severe consequences than isolated shocks due to accumulating losses and reduced coping capacity.

According to Cui & Tang (2024), households can mitigate the impact of weather shocks on consumption with savings or crop stocks. However, most rural households in Ecuador are poor, with a monthly average per capita income of USD 110 (ENEMDU Panels, 2013-2019), which falls below the cost of the consumer basket of USD 715 (ENEMDU, 2019). This financial shortfall significantly reduces the likelihood of having savings. Therefore, the first shock affects their consumption and spending capacity. When facing a second shock, resources are already insufficient, increasing their vulnerability and worsening their economic situation.

The second shock usually has more severe effects since households have exhausted or reduced their assets. According to Aragón et al. (2021), weather shocks force families to sell livestock or other goods. If, during the first shock, they had to sell these assets, in the second event, they have fewer resources to face adversity, which leaves them more vulnerable and with fewer options to recover. Moreover, these shocks lead farmers to increase the area planted (Aragón et al., 2021), which reduces the capacity of the soil to restore and decreases productivity in future harvests. If this coincides with a new shock, losses may be even greater.

On the other hand, Jagnani et al. (2020) point out that households with limited resources tend to increase the use of pesticides and reduce the use of fertilizers after an extreme event. Although this strategy may be effective in the short term, a second shock could exhaust farmers' financial capacity to acquire inputs, leaving soils less fertile and reducing future yields. This imbalance, coupled with limited investment capacity, aggravates economic losses and hinders recovery in the medium and long term. That is, facing recurrent rainfall shocks have greater negative consequences for rural households.

3. Materials and method

We run regression models with households as the observation unit, relating different welfare indicators to extreme rainfall events experienced at the local level and accounting for other relevant factors. The dependent variables are per capita household income, poverty, poverty gap, and poverty severity. The main explanatory variables are indicators of recurrent rainfall shocks in each locality, controlling for confounding factors. The data on rural households are taken from Ecuador's National Survey of Employment, Unemployment, and Underemployment (ENEMDU), conducted by the National Institute of Statistics and Censuses (INEC). Daily rainfall data are extracted from the Climate Hazards Center at the University of California, Santa Barbara (CHIRPS). The household and rainfall data are linked through the census sector code. Details of the data and the statistical approaches used are provided below.

3.1 Household data

The household data used comes from Ecuador's nations survey ENEMDU. ENEMDU is among the country's most important surveys for studying income and employment and the official source for calculating household living standards and poverty in Ecuador. The data are collected every quarter, and its sample design facilitates the construction of annual panels with specific subsamples (INEC, 2017). We use the surveys covering the period from 2013 to 2019, which provides the panel data that is representative of rural areas (INEC, 2022).

This structure allows the analysis of the same households in two annual cohorts, for example, in the first quarter of 2016 and the first quarter of 2017. For the study, we stack 13 annual panels corresponding to the different quarters from 2013 to 2019. This results in 59,969 households, each observed over two periods (119,938 observations), as shown in Table 1.

Table 1: Annual panels (number of observations at the household level)

Panel	Period	2013	2014	2015	2016	2017	2018	2019	Total
Panel 1	Q4 (2013-2014)	3,942	3,942						**7,884**
Panel 2	Q1 (2014-2015)		3,352	3,352					**6,704**
Panel 3	Q2 (2014-2015)		8,900	8,900					**17,800**
Panel 4	Q3 (2014-2015)		1,206	1,206					**2,412**
Panel 5	Q3 (2015-2016)			2,067	2,067				**4,134**
Panel 6	Q4 (2015-2016)			9,353	9,353				**18,706**
Panel 7	Q1 (2016-2017)				4,285	4,285			**8,570**
Panel 8	Q2 (2016-2017)				4,336	4,336			**8,672**
Panel 9	Q3 (2016-2017)				1,655	1,655			**3,310**
Panel 10	Q1 (2018-2019)						4,912	4,912	**9,824**
Panel 11	Q2 (2018-2019)						5,254	5,254	**10,508**
Panel 12	Q3 (2018-2019)						5,350	5,350	**10,700**
Panel 13	Q4 (2018-2019)						5,357	5,357	**10,714**
Total		**3,942**	**17,400**	**24,878**	**21,696**	**10,276**	**20,873**	**20,873**	**119,938**

Source: ENEMDU Panels, 2013-2019

Ecuador has 40,558 census sectors. Census sectors represent a group of city blocks or settlements. Specifically, in rural areas, a census sector is a delimited area consisting of one or more settlements and, on average, includes 80 to 110 households (INEC, 2020). In the surveys, the sample households are georeferenced at the level of census sectors, which allows us to identify their geographic locations and merge them with weather data.

3.2 Weather data

Rainfall shocks cause the biggest weather-related losses in rural Ecuador (Ministry of Environment, 2012). The lack of rain mainly affects the agricultural sector, the principal economic activity in rural areas. Excess rain affects agriculture but also other sectors of the economy. The Ministry of Environment (2019 & 2021) indicates that from 2010 to 2020, homes, educational institutions, roads, bridges, and crops were affected and partly destroyed by extreme precipitation events, hampering all economic and social activities.

To capture the effect of weather, we work with daily rainfall data and construct suitable rainfall shock variables. The daily precipitation data were extracted from the Climate Hazards Center at the University of California, Santa Barbara. The "CHIRPS-daily" information provides data to a spatial resolution of approximately 5 km2 (0.05° x 0.05°) and is estimated through satellite observations using infrared radiation and calibrated with ground-based weather stations worldwide (University of California, 2023).

For each area within the census sectors, we identify its centroid's geographical coordinates (latitude and longitude) and obtain the daily rainfall information of each centroid since 1981. To capture extreme weather shocks specific for each quarter, we first estimate the quarter accumulated rainfall for each census sector in the mentioned years. We use this information to calculate the quarterly z-score for accumulated rainfall as follows:

$$z - score_{it} = \frac{Acp_{it} - \overline{Acp_i}}{Acp_i^{SD}} \qquad \text{(Equation 1)}$$

Where Acp_{it} is the accumulated rainfall of census sector *i* in quarter *t*. $\overline{Acp_i}$ is the historical average (for the corresponding quarter) of accumulated rainfall in census sector *i*, and Acp_i^{SD} is the standard deviation of the accumulated rainfall (for the corresponding quarter) in census sector *i*.

We identify an extreme event when the analyzed value Acp_{it} is significantly higher or lower than the historical average for the same quarter and territory, as done in previous studies (Boansi et al., 2021; Skoufias & Vinha, 2013; Amare et al., 2018). Using z-scores and recognizing that not all deviations from the long-term mean qualify as shocks, we measure rainfall shocks with dummy variables designed to capture extreme events as follows.

Considering the z-scores from Equation 1, the dummy takes the value of 1 if in a particular census sector z>2 (excess rain) or z<-2 (lack of rain), and 0 otherwise, since both excess and lack of rain have negative consequences for households in terms of income and poverty. For each household *j*, located in census sector *i*, we then count the number of shocks the household faced. Since we observe each household in two periods, the count variable can take 0, 1, or 2 values. Using this count, we construct two additional dummies: D_1pr_{jit} which takes the value of 1 if the household *j* in census sector *i* faced one rainfall shock, and 0 otherwise, and D_2pr_{jit} which takes the value of 1 if the household faced two consecutive rainfall shocks, and 0 otherwise. These two dummies characterize recurrent rainfall shocks in our regression models with zero shocks as the reference. Details of the regression models are explained below.

3.3 Regression models

To estimate the effects of rainfall shocks on income and poverty indicators, we use panel data regression models with household fixed effects of the following type:

$$Y_{jit} = \beta_o + \beta_1 D_1 pr_{jit} + \beta_2 D_2 pr_{jit} + \gamma \boldsymbol{X_{jit}} + \delta \boldsymbol{D_t} + \boldsymbol{\theta_j} + \varepsilon_{jit} \qquad \text{(Equation 2)}$$

Where Y_{jit} is the outcome variable for household *j* in census sector *i* and period t, and D_1pr_{jit} and D_2pr_{jit} are the two dummy variables representing one and two rainfall shocks, respectively, as explained in the previous subsection. $\boldsymbol{X_{jit}}$ is a vector of control variables that may also influence income or poverty, such as household size, education, and age of the household head, and whether or not the household receives conditional cash transfers under the Ecuador's Human Development Bonus program, among others. $\boldsymbol{D_t}$ is a vector of time dummies for the different quarters from 2013 to 2019, $\boldsymbol{\theta_j}$ is a vector of household fixed effects, controlling for unobserved time-invariant heterogeneity, and ε_{jit} is a random error term.

In these models in Equation 2, we are particularly interested in the coefficients β_1 and β_2. With household income as the dependent variable, a negative and significant β_1 would indicate that one rainfall shock has a negative effect on income. A negative and significant β_2 would indicate that two consecutive rainfall shocks have a negative effect on income. We are also interested in how the size of the two coefficients compare, hypothesizing that $|\beta_2|>|\beta_1|$.

In our estimates, we use deflated per capita income expressed in logarithmic terms as dependent variables, meaning that the coefficients β_1 and β_2 can be interpreted as percentage effects. We use robust standard errors to account for possible heteroskedasticity and employ survey sampling weights such that the estimates are representative (Azzarri & Signorelli, 2020) for rural Ecuador.

We start by estimating Equation 2 with the entire rural household sample. Subsequently, we re-estimate the same model with two subsamples, namely poor and non-poor households, to gain further insights into effect heterogeneity. We hypothesize that the negative income effects of rainfall shocks are more pronounced for poor than non-poor households.

Finally, we estimate Equation 2 with different poverty indicators as dependent variables. The indicators we use belong to the Foster-Greer-Thorbecke (FGT) class of poverty indices. The FGT index for a population is calculated using Equation 3, which allows for varying the weight (α) applied to the level of the index being analysed (International Labour Organization, 2005).

$$FGT_\alpha = \frac{1}{n}\sum_{j=1}^{q}\left(\frac{p-y_j}{p}\right)^\alpha \qquad \text{(Equation 3)}$$

where n is the population size, q the number of individuals whose per capita income y is below the poverty line p, and α is a sensitivity parameter that can take values of 0, 1, or 2.

If α =0, the FGT0 is the "headcount index", meaning the proportion of the population below the poverty line (International Labour Organization, 2005). We use the official poverty line for Ecuador established for 2006 (INEC, 2008), which we update using the official consumer price index. Expressed in current US dollars, the poverty line is equivalent to a monthly per capita income of 56.64 USD, which we use to differentiate between poor and non-poor households and to calculate the headcount index. In addition, we calculate a headcount index for the extreme poverty line of 31.92 USD. For estimating Equation 2, we create a poverty dummy as the dependent variable, which takes the value 1 if per capita income is below the poverty line and 0 otherwise.

If α =1, the FGT1 is the "poverty gap", quantifying how far poor households are from the poverty line (International Labour Organization, 2005). We calculate the poverty gap for each household in the sample, which can take any value between 0 and 1. For non-poor households, the poverty gap is 0. Finally, if α =2, the FGT2 is the "squared poverty gap", which is also known as the "poverty severity" (International Labour Organization, 2005). We use the poverty gap and poverty severity for each household as dependent variables in the regression models explained in Equation 2. Note that for the poverty models, we expect positive estimates for β_1 and β_2, meaning that rainfall shocks are hypothesized to lead to rising poverty rates as well as rising poverty gaps and poverty severity.

We perform several tests to establish the validity of our estimation approaches. The test results are shown in Table A1 in the Appendix. The null hypothesis of homoskedasticity of the error terms is rejected in all models, meaning that our approach of using robust standard errors is appropriate. Likewise, the test results suggest including time-fixed effects, as we do, is preferred. Finally, the Hausman test results suggest that the null hypothesis of no unobserved heterogeneity is rejected, meaning that our fixed effects estimator is preferred over the alternative random effects estimator.

4. Results

4.1 Descriptive statistics

The primary economic activity that rural households in Ecuador are engaged in is agriculture, accounting for 65% of the sample, followed by commerce (8%), manufacturing (7%), and construction (5%). Only 24% of the rural population has formal employment (Table 2). About 74% are either working on their own farm or are informally employed, meaning they do not have social security protection. These patterns suggest that most households in rural Ecuador are quite vulnerable to climate shocks.

Table 2: Employment - rural Ecuador

Category	Percentage
Formal employment	23.77%
Informal employment	74.25%
Unemployment	1.98%

Source: ENEMDU Panels, 2013-2019

Table 3 summarizes the variables we use in our regression models. Panel A shows the dependent variables. The average monthly per capita income is around 110 USD. More than one-third of the population (35%) is affected by poverty, and 13% suffer from extreme poverty. The poverty gap and the poverty severity are 0.13 and 0.07, respectively. The lower part of Table 3 (Panel B) shows the control variables. The average household head is 51 years old and has 6.8 years of education. The average household size is 4.0.

Table 3: Summary statistics of household characteristics

	N	Mean	SD	Min	Max
Panel A: Main outcome variables					
Per capita monthly income (deflated USD)	118,948	109.92	146.51	0.12	23,155.47
Poverty (dummy)	118,948	0.35	0.48	0.00	1.00
Extreme poverty (dummy)	118,948	0.13	0.34	0.00	1.00
Poverty gap (0-1)	118,948	0.13	0.23	0.00	1.00
Poverty severity	118,948	0.07	0.16	0.00	1.00
Panel B: Household controls					
Education head of household	119,938	6.82	4.16	0.00	22.00
Age head of household head	119,929	51.05	16.26	13.00	98.00
Number of people in the household	119,938	4.00	2.08	1.00	28.00
Number of children under 5 years old	119,938	0.44	0.71	0.00	8.00
Number of older adults (65 or older)	119,938	0.34	0.63	0.00	5.00
BDH beneficiary household	119,936	0.41	0.49	0.00	1.00

Source: ENEMDU Panels, 2013-2019

Regarding rainfall patterns, Ecuador has two seasons: the rainy and dry seasons. The rainy season extends from November/December to April/May, the remaining months correspond to the dry season (Ministry of Environment, 2021). During the rainy season, the rainfall is typically abundant and can be very intense, and there is also high humidity. In the dry season, low rainfall creates a cool and dry climate. Usually, the first quarter of the year records the highest amount of rainfall, whereas the third quarter records the lowest (Figure 2). In this sense, our study compares similar periods in terms of expected rain (for example, the first quarter of 2015 vs. the first quarter of 2016), and we refer to consecutive shocks considering these seasonality cycles.

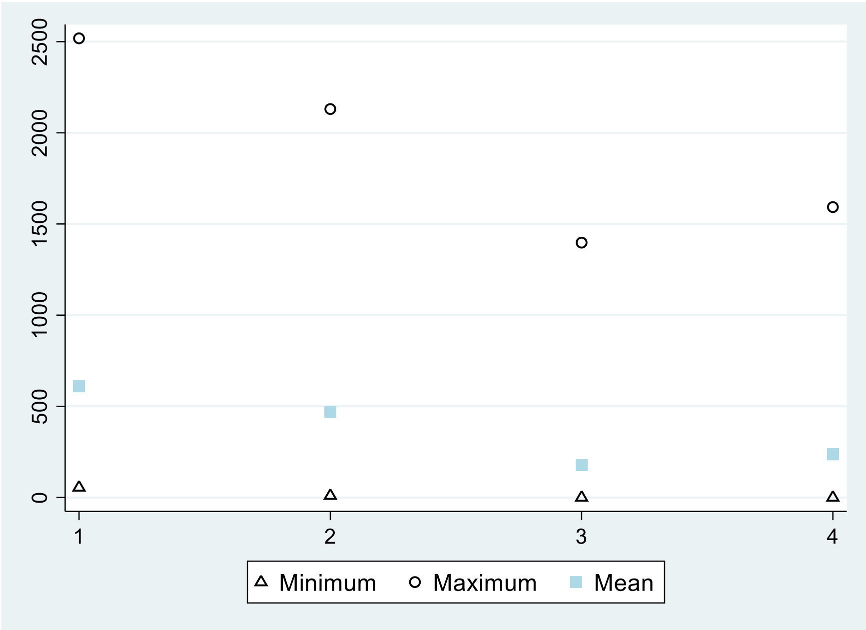


Figure 2: Quarterly accumulated precipitation (in mm for the period 1981-2020)

Source: CHIRPS (2023)

4.2 Econometric method

Income effects of rainfall shocks

Table 4 shows the estimated effects of rainfall shocks on per capita income (expressed in logarithmic terms), using fixed effects regression models as explained in Equation 2. Column (1) of Table 4 shows estimates of a model with only the rainfall shocks and no control variables included. Column (2) shows results with control variables included (full model results are shown in Table A2 in the Appendix). We mainly interpret the estimates of the model with control variables (column 2), as these are considered more reliable.

Table 4: Effects of recurrent rainfall shocks on per capita income

	(1)	(2)
One rainfall shock	-0.0879***	-0.0894***
	(0.0207)	(0.0206)
Two rainfall shocks	-0.165**	-0.133*
	(0.0687)	(0.0692)
Control variables	No	Yes
Time dummies	Yes	Yes
Observations	118,948	118,937
Number of id	59,922	59,919
R-squared	0.0060	0.0210

Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The estimate of -0.089 in column (2) of Table 4 implies that experiencing one rainfall shock reduces per capita income by approximately 9% after controlling for confounding factors. Two rainfall shocks lead to even larger income losses of 13%. The amplified magnitude suggests that the negative effects of rainfall shocks accumulate and may further worsen household welfare due to the reduced ability to recover between repeated shock events. That is, the first shock may leave households in a more vulnerable position and with fewer resources to face a subsequent second shock. Since CHIRTS (temperature) data are only available up to 2016 and not until 2019, the results of the regressions controlling for average temperature are presented in Table A2.1 in the Appendix. The results indicate the same pattern: negative effects of the first shock and more adverse impacts of the second. The temperature has no effect.

We estimate the same model with subsamples of poor and non-poor households to identify heterogeneous effects, using the official poverty line for separation. The results are presented in Table 5.

Table 5: Effects of recurrent rainfall shocks on per capita income (poor and non-poor households)

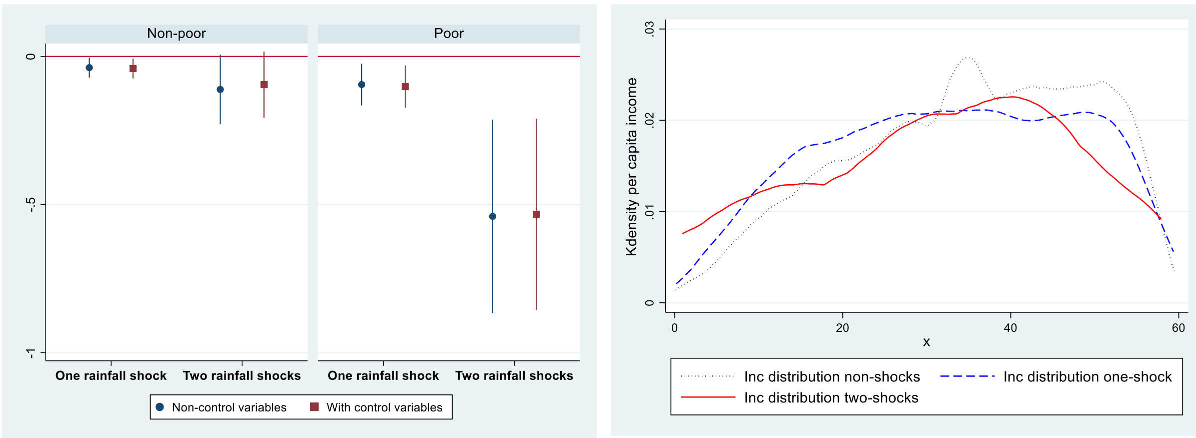
	Non-poor		Poor	
	(1)	(2)	(3)	(4)
One rainfall shock	-0.0377**	-0.0407**	-0.0949***	-0.102***
	(0.0172)	(0.017)	(0.0359)	(0.0364)
Two rainfall shocks	-0.111*	-0.0954*	-0.540***	-0.533***
	(0.06)	(0.057)	(0.166)	(0.165)
Control Variables	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes
Observations	77,203	77,194	41,745	41,743
Number of id	47,180	47,175	29,353	29,352
R-squared	0.0130	0.0310	0.0060	0.0170

Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Full model results are shown in Table A3 in the Appendix.

Rainfall shocks negatively affect the income of both poor and non-poor households. However, poor households suffer from larger income losses. One rainfall shock leads to an income loss of 4% among the non-poor and 10% among the poor. Two consecutive shocks reduce the income of non-poor households by 9.5%, yet the losses mount up to 53% for poor households.

Tables A4.1 and A4.2 in the Appendix show the impacts, including temperature (2013-2016). The results show similar patterns: an increase in poverty measures, with more adverse consequences of the second shock. The temperature has no effect.

Rainfall shocks also tend to change the income distribution among the poor, as shown in Figure 3, Panel B. There is a higher proportion of households -that have not faced rainfall shocks- with higher incomes (black line). When facing rainfall shocks, the income distribution shifts to the left, indicating a higher concentration of households with lower income values (red line).



Panel A: Confidence intervals

Panel B: Income distribution among the poor

Figure 3: Effects of recurrent rainfall shocks on income distribution

Finally, one rainfall shock significantly increases the poverty gap and severity (Table 6). These effects further intensify after two consecutive shocks. The results suggest that rainfall shocks push rural households into poverty and deteriorate their economic conditions, moving them further from the poverty line.

Table 6: Effects of recurrent rainfall shocks on per capita income

	Poverty (dummy)		Extreme poverty (dummy)		Poverty gap (0-1)		Poverty severity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
One rainfall shock	0.0366***	0.0371***	0.0282***	0.0287***	0.0231***	0.0234***	0.0174***	0.0177***
	(0.0125)	(0.0125)	(0.00987)	(0.00985)	(0.00629)	(0.00629)	(0.00473)	(0.00474)
Two rainfall shocks	0.0192	0.00483	0.0803***	0.0709***	0.0405**	0.0330*	0.0369***	0.0319***
	(0.0494)	(0.0501)	(0.0231)	(0.0235)	(0.0182)	(0.0188)	(0.0107)	(0.0111)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118,948	118,937	118,948	118,937	118,948	118,937	118,948	118,937
Number of id	59,922	59,919	59,922	59,919	59,922	59,919	59,922	59,919
R-squared	0.003	0.009	0.001	0.006	0.002	0.01	0.002	0.009

Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Full model results are shown in Table A4 in the Appendix.

5. Conclusion

Climate change with rising temperatures and more frequent weather extremes has local consequences that differ between regions, countries, and population groups within countries. This study estimated the effects of rainfall shocks – including droughts and excessive rains – on income and poverty in rural Ecuador. Rural households in Ecuador are particularly vulnerable to rainfall shocks and other extreme weather events since they are exposed to floods and droughts, have a low adaptive capacity, and economically depend on agriculture and other activities sensitive to climate variations.

Our results show that one rainfall shock reduces the per capita income of rural households in Ecuador by 9% on average. Even though the magnitude of the effects differs, the general findings are consistent with earlier studies analysing the effects in other geographic regions, including various countries in Africa and Asia (Amare & Balana, 2023; Arouri et al., 2015; Chuang, 2019; Hallegatte et al., 2018; Lokonon et al., 2015; Pleninger, 2022).

In rural Ecuador, we find that the income losses are more pronounced for poor than for non-poor households, which is also consistent with earlier research in other geographic settings (Boansi et al., 2021; Brouwer et al., 2007; Salvucci & Santos, 2020). What has not been analysed much previously is how repeated weather shocks can further aggravate economic hardships and income distribution. Our results show that a second consecutive rainfall shock amplifies the income losses dramatically, especially for poor households: a second shock reduces per capita income by 13% on average and 53% for households below the poverty line. This very large negative effect on poor households is likely related to their low resilience and recovery capacity, given their insufficient access to savings, financial services, and social protection.

We also find that rainfall shocks increase poverty rates in rural Ecuador. One rainfall shock increases poverty by 3.7 pp and extreme poverty by 2.8 pp. A second rainfall shock increases extreme poverty by even 7.0 pp. Furthermore, the estimates show that rainfall shocks significantly increase the poverty gap and severity, with larger effects associated with repeated events. That climate change and extreme weather events can increase poverty rates considerably was also shown in different countries of Africa and Asia (Azzarri & Signorelli, 2020; Baez et al., 2020; Salvucci & Santos, 2020; Skoufias et al. 2011).

Overall, our study adds to the literature on the impacts of climate change and recurrent weather shocks on income distribution and poverty in the Global South. The findings show that severe negative consequences are observed not only in Africa and Asia but also in Latin America. The estimates with representative data from rural Ecuador underline that recurrent rainfall shocks have significant adverse income effects and hurt poor population groups over-proportionally. Although our study is limited to two consecutive shocks, showing that the second has a significantly greater impact, it paves the way for future research to investigate the effects of experiencing several consecutive, cascading, and/or compounding shocks on welfare outcomes, especially as climate change is expected to increase the frequency of these extreme events.

The results have important implications for further research and policymaking. Against the backdrop of ongoing climate change, not only mitigation but also effective adaptation strategies need to be urgently developed and implemented.

The resilience and recovery capacities of poor and vulnerable households must be strengthened, and these should include climate risk insurance and safety net programs that can help low-income families recover more quickly after facing an extreme weather event. The government can implement climate risk insurances, which provide financial support to households in the wake of extreme weather events, enabling them to rebuild their livelihoods without falling deeper into poverty. Moreover, safety net programs, including conditional and unconditional cash transfers, can provide immediate relief to affected families. For instance, the Human Development Bonus (BDH), a conditional cash transfer program in Ecuador, could implement an emergency cash transfer to households affected by extreme events in addition to its regular cash transfers. For vulnerable households not covered by conditional cash transfers, delivering emergency relief funds or vouchers in anticipation of an event or immediately after its occurrence can accelerate recovery.

Given that many poor households depend on agriculture for their livelihoods, technical and institutional innovations to increase and stabilize yields are also important areas that need more policy attention. For instance, policies could promote climate-resilient crop varieties, improved irrigation systems, and sustainable land management practices. These could reduce yield variability under erratic weather conditions. At an institutional level, fostering access to agricultural extension services, training on adaptive farming techniques, and strengthening farmer cooperatives can enhance the adaptive capacity of rural communities. The data on particularly vulnerable regions and population segments are gradually improving, but more work is needed to understand the heterogeneity and design and target suitable interventions effectively. For example, poor agricultural households in the paramos. Enhanced data collection efforts are critical, especially for specific vulnerable groups.

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Appendix

Table A1: Model specification tests

Model (dependent variable)	Joint F test - Time fixed effects		Wald test - Heteroskedasticity		Hausman test		
	F(13, 59918)	Prob > F	Chi2 (59919)	Prob > Chi2	Chi2 (*)	Chi2 (*)	Prob > Chi2
Per capita income	9.58	0	7.50E+41	0	Chi2(20)	1942.51	0
Poverty	4.69	0	2.80E+41	0	Chi2(20)	2090.25	0
Extreme poverty	3.3	0	9.90E+41	0	Chi2(21)	1478.7	0
Poverty gap	5.52	0	1.80E+44	0	Chi2(21)	2376.77	0
Poverty severity	4.32	0	9.00E+41	0	Chi2(20)	4989.37	0

Table A2: Effects of recurrent rainfall shocks on per capita income

	(1)	(2)
One rainfall shock	-0.0879***	-0.0894***
	(0.0207)	(0.0206)
Two rainfall shocks	-0.165**	-0.133*
	(0.0687)	(0.0692)
Education head of household		0.00780***
		(0.00246)
Age head of household		0.00198*
		(0.00103)
Number of people in the household		-0.0562***
		(0.00564)
Number of children under 5 years old		-0.0705***
		(0.0126)
Number of older adults (65 or older)		-0.0366*
		(0.019)
BDH beneficiary household		0.105***
		(0.0157)
Time dummies	Yes	Yes
Observations	118,948	118,937
Number of id	59,922	59,919
R-squared	0.0060	0.0210

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2.1: Effects of recurrent rainfall shocks on per capita income (2013-2016) without and with temperature

	Without temperature		With temperature	
One rainfall shock	-0.0843***	-0.0851***	-0.0795***	-0.0817***
	-0.0268	-0.0266	-0.0276	-0.0274
Two rainfall shocks	-0.203*	-0.154	-0.203*	-0.154
	-0.107	-0.104	-0.107	-0.104
Average temperature			-0.0133	-0.0096
			-0.018	-0.0178
Control variables	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes
Observations	67,315	67,308	67,315	67,308
Number of id	38,973	38,971	38,973	38,971
R-squared	0.0120	0.0240	0.0120	0.0240

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Effects of recurrent rainfall shocks on income (poor and non-poor households)

	Non-poor		Poor	
	(1)	(2)	(1)	(2)
One rainfall shock	-0.0377**	-0.0407**	-0.0949***	-0.102***
	(0.0172)	(0.017)	(0.0359)	(0.0364)
Two rainfall shocks	-0.111*	-0.0954*	-0.540***	-0.533***
	(0.06)	(0.057)	(0.166)	(0.165)
Education head of household		0.00840***		0.000468
		(0.00255)		(0.00483)
Age head of household		0.000918		0.00113
		(0.000946)		(0.00216)
Number of people in the household		-0.0532***		-0.0174*
		(0.00568)		(0.0105)
Number of children under 5 years old		-0.0397***		-0.0534**
		(0.0137)		(0.0216)
Number of older adults (65 or older)		-0.0214		-0.0418
		(0.0175)		(0.0446)
BDH beneficiary household		-0.0236*		0.162***
		(0.0143)		(0.0342)
Time dummies	Yes	Yes	Yes	Yes
Observations	77,203	77,194	41,745	41,743
Number of id	47,180	47,175	29,353	29,352
R-squared	0.0130	0.0310	0.0060	0.0170

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Effects of recurrent rainfall shocks on poverty, poverty gap, and poverty severity

	Poverty (dummy)		Extreme poverty (dummy)		Poverty gap (0-1)		Poverty severity	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
One rainfall shock	0.0366***	0.0371***	0.0282***	0.0287***	0.0231***	0.0234***	0.0174***	0.0177***
	(0.0125)	(0.0125)	(0.00987)	(0.00985)	(0.00629)	(0.00629)	(0.00473)	(0.00474)
Two rainfall shocks	0.0192	0.00483	0.0803***	0.0709***	0.0405**	0.0330*	0.0369***	0.0319***
	(0.0494)	(0.0501)	(0.0231)	(0.0235)	(0.0182)	(0.0188)	(0.0107)	(0.0111)
Education head of household		-0.0037**		-5.98E-05		-0.00086		-0.00013
		(0.00162)		(0.00128)		(0.000735)		(0.000532)
Age head of household		-0.00129*		-0.00086		-0.000554*		-0.00033
		(0.000728)		(0.000568)		(0.000329)		(0.000225)
Number of people in the household		0.0165***		0.0102***		0.00833***		0.00549***
		(0.00359)		(0.00276)		(0.00171)		(0.00128)
Number of children under 5 years old		0.0420***		0.0303***		0.0225***		0.0149***
		(0.00855)		(0.0073)		(0.00434)		(0.00329)
Number of older adults (65 or older)		0.015		0.00317		0.00104		0.000537
		(0.012)		(0.00898)		(0.00583)		(0.00455)
BDH beneficiary household		-0.067***		-0.0472***		-0.0386***		-0.0276***
		(0.0105)		(0.0085)		(0.00529)		(0.00417)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118,948	118,937	118,948	118,937	118,948	118,937	118,948	118,937
Number of id	59,922	59,919	59,922	59,919	59,922	59,919	59,922	59,919
R-squared	0.003	0.009	0.001	0.006	0.002	0.01	0.002	0.009

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.1: Effects of recurrent rainfall shocks on poverty, poverty gap, and poverty severity (2013-2016) without temperature

	Poverty (dummy)		Extreme poverty (dummy)		Poverty gap (0-1)		Poverty severity	
One rainfall shock	0.0401**	0.0405**	0.0393***	0.0399***	0.0292***	0.0296***	0.0204***	0.0207***
	-0.016	-0.016	-0.0143	-0.0143	-0.00889	-0.00885	-0.00698	-0.00694
Two rainfall shocks	0.0777	0.06	0.158***	0.147***	0.0922***	0.0830***	0.0738***	0.0679***
	-0.0908	-0.0908	-0.0559	-0.0567	-0.0311	-0.0316	-0.0213	-0.0217
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,315	67,308	67,315	67,308	67,315	67,308	67,315	67,308
Number of id	38,973	38,971	38,973	38,971	38,973	38,971	38,973	38,971
R-squared	0.0040	0.0090	0.0010	0.0040	0.0030	0.0080	0.0020	0.0060

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.2: Effects of recurrent rainfall shocks on poverty, poverty gap, and poverty severity (2013-2016) with temperature

	Poverty (dummy)		Extreme poverty (dummy)		Poverty gap (0-1)		Poverty severity	
One rainfall shock	0.0330**	0.0340**	0.0394***	0.0403***	0.0278***	0.0285***	0.0199***	0.0204***
	-0.0167	-0.0167	-0.0146	-0.0146	-0.0091	-0.00907	-0.00709	-0.00706
Two rainfall shocks	0.0784	0.0607	0.158***	0.147***	0.0923***	0.0832***	0.0739***	0.0680***
	-0.0908	-0.0908	-0.0559	-0.0567	-0.0311	-0.0316	-0.0213	-0.0217
Average temperature	0.0201*	0.0184	-0.000294	-0.00123	0.00402	0.00325	0.00143	0.000942
	-0.0116	-0.0115	-0.00945	-0.00944	-0.00944	-0.00552	-0.00425	-0.00423
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,315	67,308	67,315	67,308	67,315	67,308	67,315	67,308
Number of id	38,973	38,971	38,973	38,971	38,973	38,971	38,973	38,971
R-squared	0.0040	0.0100	0.0010	0.0040	0.0030	0.0080	0.0020	0.0070

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1