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Rainfall shocks push people away from the poverty line, making them poorer: Evidence from urban Ecuador

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A B S T R A C T

This study seeks to deepen the understanding of the interactions between weather extremes and vulnerable groups in urban areas. We use annual panels of household surveys from 2007 to 2019, weather information, and geographical characteristics of the territories in Ecuador to examine how rainfall shocks affect households' poverty levels. By applying fixed effects models, we find that rainfall shocks, including excess and lack of rain, significantly worsen socioeconomic conditions, pushing poor urban households further down into poverty. These events disproportionately affect women, who are overrepresented in the informal labor market, and households living in highly susceptible areas, where exposure to environmental hazards intersects with economic vulnerability. Families in the lowest percentiles are most affected, underscoring their limited resilience and adaptive capacity. This study provides insights into the effects of rainfall shocks on disadvantaged urban populations in low and middle-income countries by integrating weather data, geographical characteristics, and socioeconomic vulnerabilities into the analysis. It offers a more comprehensive understanding of how weather shocks intersect with multiple dimensions of vulnerability, particularly for women and households in highly susceptible areas who are also experiencing poverty. Furthermore, it emphasizes the need for targeted interventions and resilience-building strategies to mitigate these adverse effects, especially for vulnerable populations.

1. Introduction

Although climate change impacts populations worldwide, existing research has mainly focused on rural areas [1]. However, the high density and rapid growth of urban settings increase their exposure to weather extremes, intensifying the challenges faced by disadvantaged groups [2]. These challenges are interconnected with urban poverty, shaped by precarious employment, spatial segregation, and inadequate infrastructure [3,4].

The urban poor are often excluded from the formal labor market. High informality, in which women are overrepresented, means low and unstable incomes, limited access to credit, and lack of social security or savings [2,5]. This erodes their economic resilience and, combined with low and poor-quality education, restricts social mobility and traps families in poverty [5]. In addition, poor neighborhoods are often concentrated in urban informal settlements, with insecure tenure, overcrowding, and low-quality housing that violates building regulations [2,6]. These settlements lack proper infrastructure, roads, essential services, drainage systems, and

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transport, restricting access to jobs, education, and healthcare. They are often located in areas susceptible to natural hazards or illegal land [2,7,8].

Informal workers and households in highly susceptible settlements are significantly exposed to natural hazards [2,3]. The informal sector, including small trade businesses and street vending—overrepresented by women—is severely impacted by extreme weather events, which restrict mobility, reduce clientele and employment, lower income, destroy assets, and exacerbate economic insecurity [3,5]. Likewise, lacking affordable alternatives, low-income families settle in flood-prone lowlands or landslide-prone slopes, increasing their exposure to weather extremes [9,10]. This condition, combined with their precarious infrastructure, inadequate housing, and poor drainage systems, aggravates the impact of these weather events [2]. Climate change causes economic losses, reduces incomes, and exacerbates urban poverty, affecting especially disadvantaged groups, such as women and those in highly susceptible areas [11–13].

Ecuador is vulnerable to climate variability and change due to its geographic, oceanographic, climatic, and socioeconomic characteristics [14], with 96 % of the urban population located in regions exposed to natural hazards [15]. Droughts, floods, and landslides are the most impactful extreme events, both in terms of frequency and their human, social, and economic consequences [16–18]. Climate variability has particularly affected key ecosystems such as the Andean paramo, reducing water flow and compromising access to drinking water [19]. In addition, inadequate land-use planning, lack of regulation, and disorganized urban expansion have led to the growth of informal settlements in areas susceptible to landslides, droughts, and floods [15,18]. In this context, many urban poor populations lack the conditions to adapt effectively to extreme events [20]. Climate change not only slows poverty reduction [21] but also deepens existing vulnerabilities and social inequalities [18].

In Nigeria, floods hinder community development and increase urban poverty [22]. In the Philippines, rainfall shocks reduce household income and worsen poverty [13]. Severe tropical storms lower consumption by 12.6 % in Guatemala [23]. Similarly, in Uganda, droughts and floods decreased urban consumption by 17 %, with a greater impact on female-led households compared to male-led ones [24]. Poor people in informal settlements face greater human and material losses from floods [9].

The existing literature in urban areas relies on self-reported information on weather extremes [22,24], lacks household-level data [12], or primarily focuses on aggregate analyses without differentiating between poverty levels [10]. However, understanding the impact of rainfall shocks on urban populations requires considering factors that increase vulnerability, including the sex of the head of household and exposure to environmental hazards, both of which are aggravated by their poverty level. We address this critical gap by identifying the causal effect of rainfall shocks, integrating simultaneously household-level panel data, rainfall information, susceptibility to floods, droughts, or landslides, as well as demographic characteristics, and information on income percentiles.

This study estimates the heterogeneous effects of rainfall shocks on the distance to the poverty line in Ecuador, incorporating multidimensional aspects of urban poverty. This approach allows us to analyze intersectional vulnerabilities, including the compounded risks of being both a woman and poor, or residing in highly susceptible areas while facing economic hardship. This contribution advances the literature by offering a more comprehensive perspective on the impacts of rainfall shocks on urban poverty, considering disadvantaged groups in the context of climate change. Focusing on Ecuador (2007–2019), this study also contributes to the scarce literature on climate change and poverty in the region, where extreme events have severe consequences. For instance, between 2000 and 2022, floods were the most common disaster in Latin America, impacting 49 million people and causing approximately $28 billion in damages. Meanwhile, droughts affected the most people, over 53 million, causing $22 billion in damages [25].

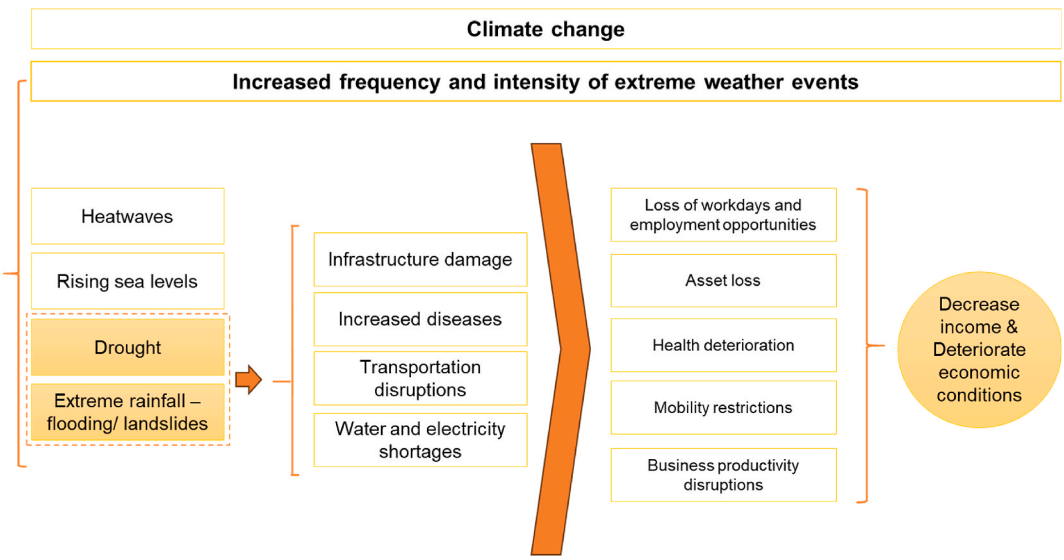

Fig. 1. Climate change impacts on household income and poverty levels.
Source: Author's elaboration based on literature review

The rest of the document is structured as follows. The conceptual framework (Section 2) details the pathways by which weather shocks affect household income poverty. Section 3, Material and Methods, presents the data and methodology used, followed by Section 4, which shows our findings. The paper concludes in Section 5.

2. Conceptual framework

Climate change is expected to increase the intensity and frequency of several hazards, including heat waves, sea-level rise, drought, and extreme rainfall [26,27], as shown in Fig. 1. Considering the analytical framework of Climate Change and Poverty developed by Hallegatte et al. [28] and connecting it to income, poverty is determined by assets, productivity, and opportunities. Through these channels, external factors such as climate change can impact income and poverty. Extreme weather events lead to asset losses, including financial, physical, human, and social capital, as well as public goods and infrastructure accessible to households. Additionally, extreme climate conditions affect labor productivity by reducing working hours and decreasing the returns on household assets. These external factors restrict the range of productive activities available to households, limiting their economic opportunities and reducing their income. This section analyzes some of these channels through which rainfall shocks—including both excess and lack of rain—affect income and exacerbate economic conditions.

Extreme rainfall, which exacerbates the hazards of floods and landslides, damages or destroys the infrastructure, including housing and businesses, contaminates water supplies, and disrupts transport networks [7,27,29,30]. These disruptions negatively affect households by limiting employment opportunities, causing asset loss, interrupting business activities, restricting mobility, and increasing health risks from contaminated water and waterborne diseases such as typhoid, dengue, cholera, and various infections [27,29].

The lack of rainfall also impacts urban populations by causing electricity shortages (due to reduced hydropower generation), increasing the risk of water contamination and waterborne diseases, and reducing water availability [27,29,30]. For example, in the Andean paramo—a key water source—decreasing water flows, combined with urban growth, lead to serious challenges in providing water for human consumption [19,31]. These conditions disrupt business productivity, decrease employment opportunities, and deteriorate health [30].

As a result, such consequences translate into lower income. Heavy rainfall restricts workers' mobility, particularly for informal workers dependent on daily labor, reducing their earnings [3]. Asset loss disrupts livelihoods by causing loss of businesses or workdays. Health impacts—such as illnesses or caregiving responsibilities—often prevent individuals from working, further decreasing their earnings and straining household resources [28,32]. Moreover, prolonged power outages hinder business operations, often forcing companies to reduce production hours or temporarily close, leading to job losses and decreased household incomes [33].

The impacts are not evenly distributed, disproportionately affecting disadvantaged populations. First, poorer households are often more exposed to extreme climate events, as many reside in highly susceptible areas and lack essential services, proper drainage systems, and quality housing. Second, they have fewer savings, limited access to credit or insurance, and receive less state assistance. Third, when disasters occur, these households suffer greater losses relative to their total wealth [5]. These factors significantly limit their ability to recover and worsen the consequences they face [26,29,34].

Rainfall shocks affect urban household incomes through various channels. In this context, this study adopts an income-based poverty approach. To estimate how extreme weather events impact the economic conditions, we use the distance to the poverty line $\left(\frac{V_{ji}-z}{z}\right)$, where we compare the household per capita income V_{ji} to the poverty line z. According to the National Institute of Statistics and Censuses [35] , per capita income measures economic well-being that captures all current household income. The poverty line represents the minimum available income an individual needs in order not to be considered poor [36].

The distance to the poverty line indicates how far (or close) households are from the poverty threshold, with negative values representing households below the poverty line and positive values for those above it. For example, a value of −0.2 means a household is 20 % below the poverty line, while a value of 0.50 indicates it is 50 % above. Using this measure, we examine how rainfall shocks alter the distance to the poverty line by influencing household income, accounting for—but not limited—to the previously described pathways through which urban income is affected. Our hypothesis is that these effects are more severe for certain socioeconomic groups, such as low-income households, female-led households, or those residing in areas highly susceptible to landslides, floods, or droughts.

3. Materials and method

We use fixed effects to analyze how weather shocks impact households in urban Ecuador. As mentioned, the dependent variable is the distance to the poverty line. The independent variables are the rainfall shocks in each census sector where households are located, as well as household characteristics. We combine rainfall data, household surveys, and geographic information. The data are linked using territorial codes, creating a comprehensive database that includes household socioeconomic characteristics, rainfall shocks, and geographic information on landslide, flood, and drought susceptibility within these territories.

3.1. Data

3.1.1. Household

Household data come from the National Survey on Employment, Unemployment, and Underemployment (ENEMDU). The survey is the official source for examining income distribution, poverty levels, employment conditions, and job market characteristics in Ecuador. The ENEMDU is conducted quarterly nationwide, ensuring national and urban representation [37]. Between 2007 and 2019, the survey was developed using a conglomerate[1] panel approach, which helps create annual panels from a subsample and allows the examination of the same observation units across different yearly cohorts. For example, we can observe the same households in two distinct periods: the first quarter of 2016 and the first quarter of 2017.

In this study, we focus on urban households, for which we harmonize and pool 25 annual panels corresponding to different quarters from 2007 to 2019. This has resulted in a unique dataset with 142,739 households observed over two periods, comprising 285,478 observations, as shown in Table A1 in the Appendix.

The survey georeferences households at the census sector level, allowing us to identify the spatial location of households within the annual panels. In the urban area, a census sector encompasses a contiguous area that may include one or more city blocks, typically comprising an average of 150 households [38].

3.1.2. Weather

To capture the effect of extreme weather events, we estimate rainfall shocks, as done in previous studies [39–41]. The daily rainfall data is obtained from the Climate Hazards Center at the University of California, Santa Barbara. The “CHIRPS-daily” dataset offers information at a spatial resolution of approximately 5 km^2 ($0.05^\circ \times 0.05^\circ$), utilizing a combination of satellite observation, infrared data, and weather station records across the globe [42].

We identify the centroid’s geographical coordinates (longitude and latitude) within each census sector and gather the daily precipitation data from 1981. To capture the shocks for the corresponding quarter in each location, we estimate the accumulated quarterly rainfall for each census sector Acp_{it}. Then, we calculate the quarterly z-score for accumulated rainfall, as shown in Equation (1).

$$z - score_{it} = \frac{Acp_{it} - \overline{Acp_{it}}}{Acp_{it}^{SD}} \tag{1}$$

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

Based on the z-score values and recognizing that not all deviations from the long-term mean qualify as shocks, we measure rainfall shocks with a dummy variable that takes the value of 1 if the z-score of the census sector i in quarter t is greater than 2 (positive rainfall shock) or lower than -2 (negative rainfall shock), and 0 otherwise. This approach considers the total effects of excess or lack of rain.

3.1.3. Geographic

We obtain geographic information on land susceptibility to floods, droughts, and landslides from the Geoinformation Generation Project for Territorial Management (GGP) and Threat Analysis Against Mass Movements in Ecuador (TAM) in collaboration with the Ecuadorian Space Institute; the Ministry of Agriculture, Livestock, Aquaculture, and Fisheries; the General Coordination of the National Information System; and the National Risk and Emergency Management Service.

The Geoinformation Generation Project (GGP) generated information to identify areas susceptible to droughts and floods, while the National Risk and Emergency Management Service provided information on landslides. The maps cartographically identify areas across the country susceptible to floods, droughts, and landslides, and classify the territory based on these events into categories of high, medium, low, or no susceptibility.

For floods, the GGP analyzed the soil and climate or weather characteristics: topography (relief and slopes), lithology, geomorphology, pedology, soil forms (valleys, slopes), and the frequency and location of precipitation. This analysis classified Ecuadorian territory into high, medium, low, and non-susceptible flood zones. High susceptibility represents the territories where cyclic floods occur every year during the rainy season, and areas without susceptibility are not prone to flooding [43].

For droughts, the GGP studied precipitation patterns, temperature, evapotranspiration, humidity, soil shapes, and relief (valleys, slopes). According to the analysis, the project classified the territory as high, medium, low, or non-susceptible to drought. High susceptibility is defined when the probability of a drought occurring is greater than 45 %, and no threat is determined when the probability of occurrence is zero [44].

To establish the level of susceptibility of mass movements (landslides), the TAM studied the variables of structural density (geological faults, structural lineaments), slope and soil texture, geology (lithology), precipitation, effective depth, and stability. According to the analysis, the Risk Service classified the territory as having very high, high, medium, low, or no landslide susceptibility. Territories with very high landslide susceptibility typically feature steep slopes, fractured rocks, lack of vegetation cover, and eroded soils that are neither cohesive nor compact. No susceptibility corresponds to stable territories with no probability of mass movements occurring, characterized by flat to gentle terrain slopes of no more than 5 % [45].

Using this information, we identify highly susceptible and non-susceptible territories. For each parish, we calculate the percentage

[1] Group of homes that belong to the same district.

of land with high or very high susceptibility to flooding, droughts, or landslides. For example, Rioverde in the province of Esmeraldas has 19 % of its territory with very high or high susceptibility to landslides, 6 % with high susceptibility to flooding, and 0.1 % with high susceptibility to drought. San Joaquin, in Cuenca, has 58 % of its territory with high susceptibility to landslides, 2 % with high susceptibility to flooding, and 0 % with high susceptibility to drought. We then identify highly susceptible territories as those where the parish has high or very high susceptibility to drought, flooding, or landslide in at least 50 % of its area. In our example, Rioverde is a non-susceptible territory, and San Joaquin is considered highly susceptible.

3.2. Econometric method

Weather extremes reduce income and elevate poverty levels in urban areas by limiting job opportunities, destroying assets, deteriorating health, restricting mobility, and disrupting businesses, where poor households are more affected [27,29,30]. In this context, we employ fixed effects to estimate the extent to which rainfall shocks worsen households' economic conditions (Equation (2)). This approach eliminates the effect of time-invariant unobserved heterogeneity among households and isolates the impact of rainfall shocks on household location.

$$Y_{jit} = \beta_o + \beta_1 Dpr_{jit} + \gamma X_{jit} + \delta D_t + \theta_j + \varepsilon_{jit} \tag{2}$$

Where Y_{jit} corresponds to the distance to the poverty line for household j (located in the census sector i) in the quarter t. Dpr_{jit} is the dummy representing facing a rainfall shock (excess or scarce rain), and X_{jit} is the vector of independent variables for household j in the period t. We include household characteristics such as the education and age of the household head, the number of household members, the number of elderly (older than 65), and the number of children (younger than 5), where the last two help capture household dependency burdens. We also incorporate temporal dummies for each quarter: Dt.

We calculate the distance to the poverty line as the ratio $\left(\frac{V_{ji}-z}{z}\right)$, which corresponds to the difference between the household per capita income V_{ji} and the threshold (poverty line z), divided by the poverty line z. The ratio represents the percentage of how close (or far) families are to the poverty line. Values nearing -1 indicate that households are significantly below the poverty line (poorer), while those approaching 0 signify being nearly at the poverty line (less poor). Wealthier households have positive values. This metric offers deeper insight into how far people are from reaching the income threshold, assessing the depth of their poverty.

We use Ecuador's official poverty line, which is based on the consumption poverty line from the fifth Living Conditions Survey (ECV-5) and is updated for each period using the Consumer Price Index, as established by the National Institute of Statistics and Censuses [46]. This approach employs data from household surveys and their sampling weights to estimate the model, ensuring the representativeness and statistical validity of the estimates [47].

In addition, to better understand the causal mechanism through which the poverty line is affected, we analyze how rainfall shocks impact household per capita income, using Equation (2). Where Y_{jit} represents the per capita income of household j (located in census sector i) in quarter t. This analysis strengthens the connection between the conceptual framework and the empirical findings, aiming to show that climate shocks could negatively affect income and, consequently, push vulnerable households below the poverty line.

The study also evaluates differentiated or heterogeneous effects of rainfall shocks on the urban population. First, we identify the vulnerable groups mentioned in the literature: women and people living in highly susceptible areas to natural hazards. Second, to assess whether the most disadvantaged are more affected, we analyze subsamples based on income percentiles 10, 25, 50, and 75, applying the model described in Equation (2). It is important to note that we have stacked 25 bases, providing sufficient data to perform these subsample analyses.

We conducted several tests to validate our estimation method. The results are presented in Table A2 of the Appendix. We use robust standard errors because we reject the null hypothesis of homoscedastic error terms across all models. Additionally, the test outcomes favor the inclusion of time-fixed effects, which we have incorporated into our analysis. Finally, the Hausman test led us to reject the null hypothesis of no unobserved heterogeneity, indicating a preference for our fixed-effects estimator over the random-effects model.

Table 1
Summary statistics - Household characteristics.

	N	Mean	SD	Min	Max
Panel A: Outcome variable					
Distance to the poverty line	285,478	2.55	4.58	−1.00	736.19
Per capita household income	285,478	201.25	260.35	0.22	42924.77
Panel B: Household controls					
Rainfall shock	*288,568*	*0.042*	*0.20*	-	*1.00*
Education head of household	288,568	10.45	4.89	–	23.00
Age head of household	288,534	50.85	15.32	14.00	98.00
Number of people in the household	288,568	3.81	1.91	1.00	26.00
Number of children under 5 years old	288,568	0.37	0.65	–	7.00
Number of older adults (65 or older)	288,568	0.28	0.57	–	5.00

Source: National Institute of Statistics and Censuses [48]

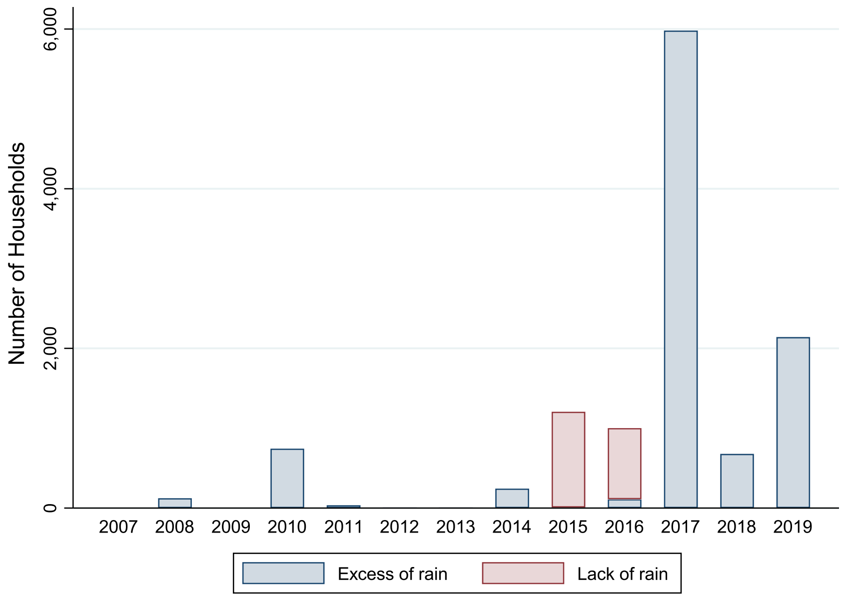

Fig. 2. Households facing rainfall shocks per year.
Source: National Institute of Statistics and Censuses [48]

4. Results

4.1. Descriptive statistics

To estimate how much rainfall shocks affect households in urban Ecuador, we consider the variables described in Table 1. Panel A shows the dependent variables, the distance to the poverty line and per capita household income, and panel B shows the independent variables: rainfall shocks, the education and age of the head of household, the number of people in the household, the number of children younger than five years, and the number of adults older than 65.

The distance to the poverty line, on average, is 2.55. That is, the urban population, in general, is above the poverty line. The average monthly per capita household income is $201.25. According to the merged household and weather data, around 4 % of households face rainfall shocks. Families are more impacted by excessive rainfall than by its scarcity, with 2017 experiencing the highest number of these weather extremes (Fig. 2). From 2007 to 2019, the average education level of the head of the household was 10.45 years, and the average age was 50.85 years. The average household size is 3.81 individuals with 0.37 children under five years old. Considering households with at least one child under five, the average is 1.28.

In addition, to understand the context of the urban area, as shown in Fig. 3 – Panel A, the main economic activities are commerce (22.18 %), manufacturing (13.35 %), transportation and storage (9.41 %), construction (9.18 %), and agriculture (8.74 %), which together contribute 62.86 % [48]. Regarding employment, 58.51 % of the population benefits from formal employment. However, underemployment affects 38.57 % of workers, implying that a considerable segment of the population may face inadequate or insufficient working conditions despite employment (Fig. 3 – Panel B). The unemployment rate is 2.92 %. Urban poverty reaches 13.74 %, and 3.74 % of the population is extremely poor.

Lower-income households face more adverse working conditions. The average per capita income in the poor population is $38.96, and the distance to the poverty line is −0.31; on average, poor people are 31 % below the poverty line. Only 14.95 % have formal employment, and 78.76 % are underemployed. The unemployment rate in this segment is 6.3 %. For poor women, 87.42 % are underemployed, 8.35 % are unemployed, and only 4.23 % are formally employed, as presented in Fig. 3 – Panel B.

At the national level, 34.4 % of urban parishes have at least half of their territory classified as highly susceptible to floods, droughts, or landslides. Among the households analyzed, 54.70 % reside in these highly susceptible territories. Ecuador is crossed by the Andes mountain range, which is why the areas most prone to landslides (in brown) are concentrated along this mountain range in the middle of the country (as seen in Fig. 4). Areas with high susceptibility to flooding (in green) are mainly located along Ecuador's south-eastern coast. Meanwhile, areas highly susceptible to drought (in beige) appear around the Ecuadorian coastline. We analyze the effects of rainfall shocks on urban households living in areas that are highly susceptible to floods, droughts, or landslides (in brown, green, and beige) to identify whether these conditions increase their vulnerability and, consequently, amplify the impacts of rainfall shocks.

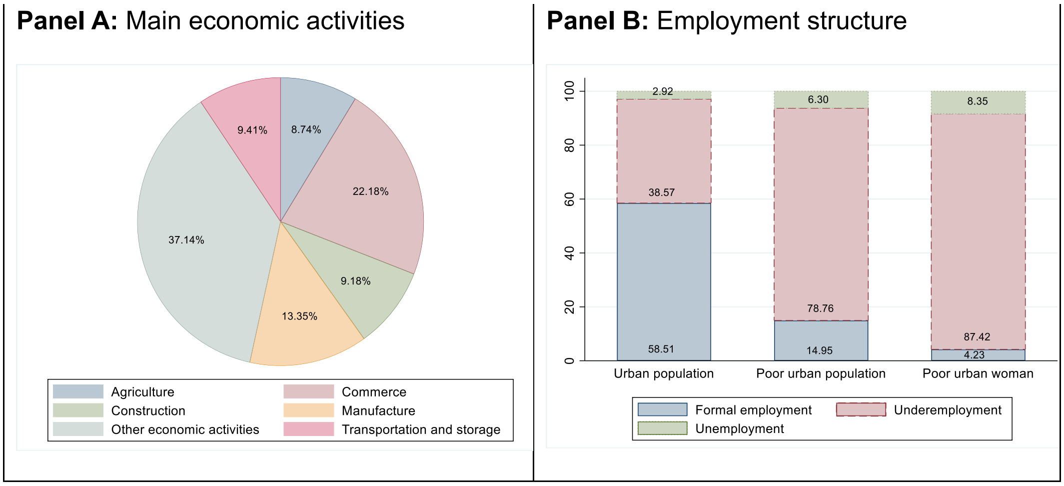

Fig. 3. Urban economy.
Source: National Institute of Statistics and Censuses [48]

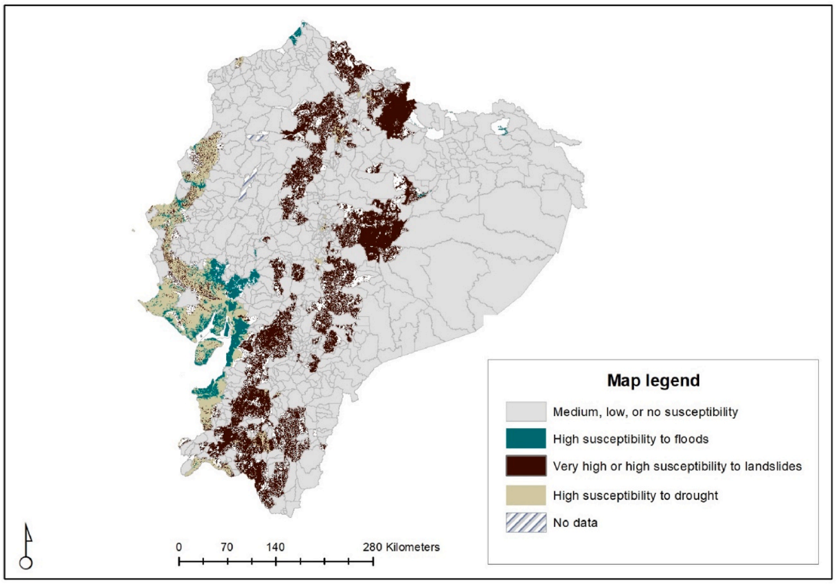

Fig. 4. Map of high susceptibility to floods, droughts, or landslides – Ecuador.
Source: Undersecretariat for Risk Information and Analysis Management [45] and the Ecuadorian Space Institute, Ministry of Agriculture, Livestock, Aquaculture and Fisheries, and National Information System Coordination [43,44]

There are territories that, due to their geographical conditions, exhibit high susceptibility to these three hazards and are also densely populated. For example, Guayas is the most populous province in Ecuador, and as shown in Fig. 5, a significant portion of its territory is highly susceptible to droughts, floods, or landslides. These conditions, combined with the fact that households may also be exposed to rainfall shocks—whether due to excessive rain or a lack of it—can severely impact people, highlighting the importance of incorporating geographical information into weather analysis.

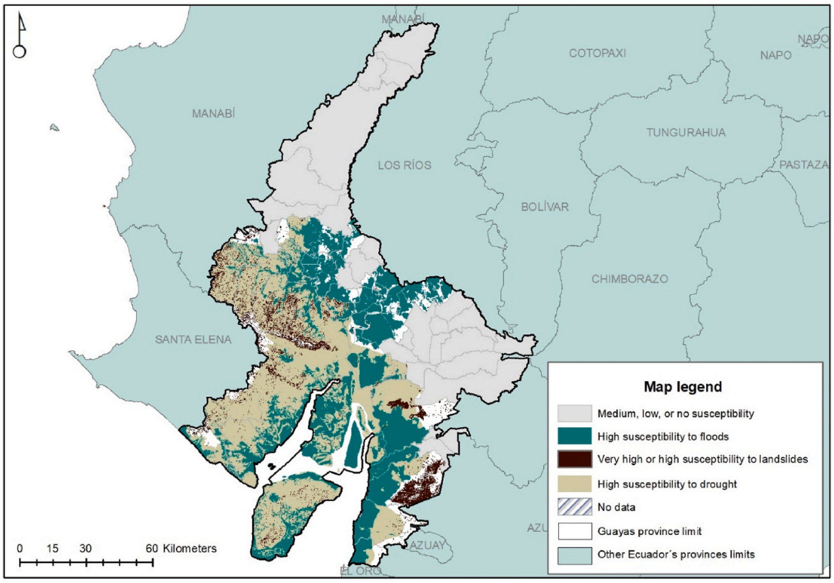

Fig. 5. Map of high susceptibility to floods, droughts, or landslides – Guayas Province.
Source: Undersecretariat for Risk Information [45] and Analysis Management and the Ecuadorian Space Institute, Ministry of Agriculture, Livestock, Aquaculture and Fisheries, and National Information System Coordination [43,44]

Table 2
Effect of rainfall shocks on the distance to the poverty line.

	Urban Area (1)	Per10 (2)	Per25 (3)	Per50 (4)	Per75 (5)	Urban Area (6)	Per10 (7)	Per25 (8)	Per50 (9)	Per75 (10)
Rainfall shock	0.0769	−0.0953 ***	−0.0705 ***	−0.0385 **	−0.029	0.084	−0.0980 ***	−0.0725 ***	−0.0376 **	−0.03
	(1.19)	(-3.19)	(-3.58)	(-2.19)	(-1.61)	(1.3)	(-3.34)	(-3.69)	(-2.14)	(-1.57)
Control Variables	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285478	16968	50866	118134	196525	285446	16964	50856	118115	196501
Adjusted R-squared	0.001	0.036	0.01	0.006	0.004	0.008	0.04	0.013	0.012	0.019

t statistics in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.
The complete table with the results of the control variables is found in Table A3 in the Appendix.

4.2. *Econometric method*

Table 2 presents the results of the econometric model (Equation (2)) based on the distance to the poverty line. The first five columns do not include control variables: Column 1 shows the impact on the total urban area, and Columns 2 to 5 show the impact on the different percentiles: 10, 25, 50, and 75. Columns 6 to 10 present the results, including control variables, for the total urban area and the different percentiles.

The analysis reveals a significant negative impact of rainfall shocks (excessive rain or a lack of it) on the distance to the poverty line, with stronger effects on the lowest income percentiles. This finding remains consistent under various model specifications (with and without control variables).

Weather extremes have heterogeneous effects across population segments. While we observe a non-significant effect in the urban area in general (Column 6), the results show an inverse and significant relationship in the lowest income percentiles. Rainfall shocks increase the distance from the poverty line for households in the 10th, 25th, and 50th percentiles. The gap widens by −9.8 percentage points for the 10th percentile (Column 7), −7.2 percentage points for the 25th percentile (column 8), and −3.8 percentage points for the 50th percentile (Column 9).

As shown in Fig. 6, Panel A, lower-income households are disproportionately affected. They are more vulnerable to these climatic

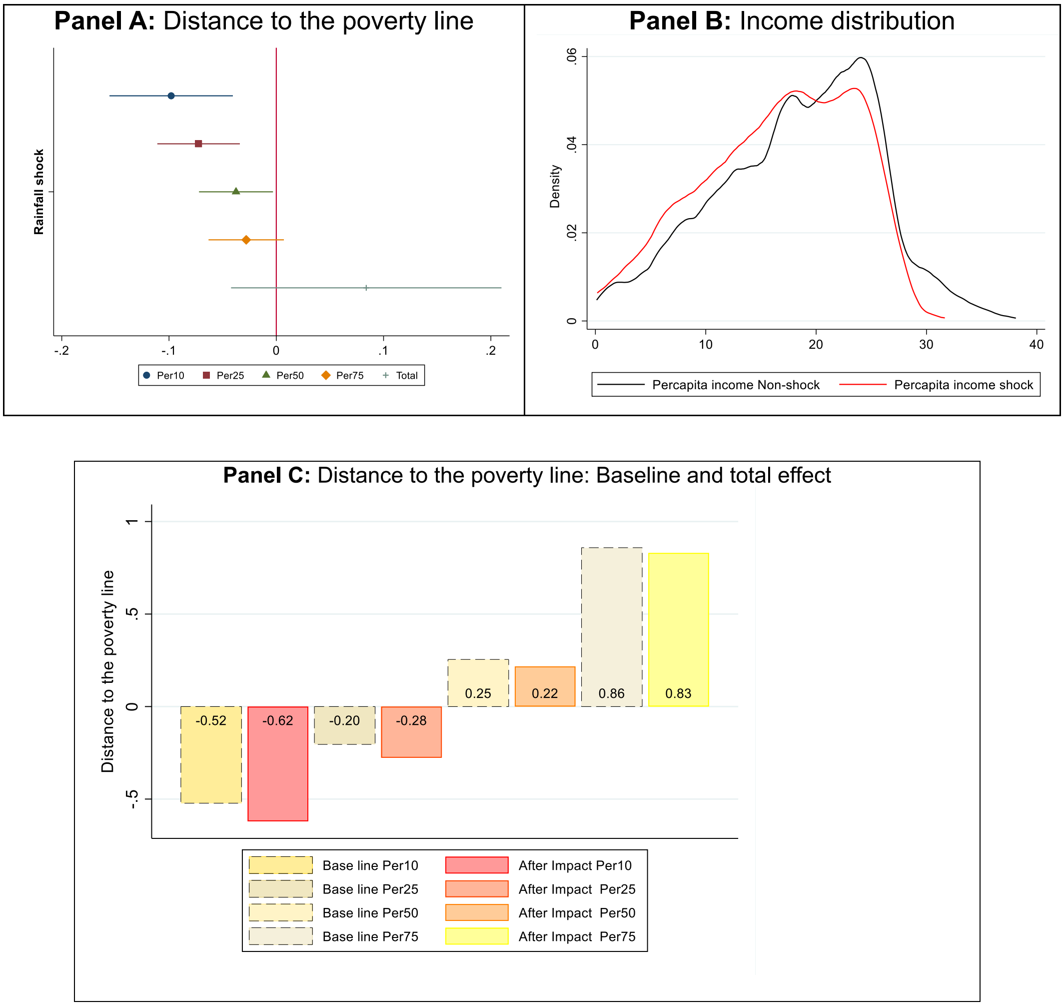

Fig. 6. Effect of rainfall shocks on the distance to the poverty line and income distribution.

events, resulting in income distribution changes for those facing a rainfall shock (Fig. 6, Panel B). As illustrated in Fig. 6, Panel C, the 10th percentile is, on average, 52 % below the poverty line. However, when exposed to a rainfall shock, their position shifts to 62 % below the poverty line, highlighting the disproportionate impact experienced by this income group compared to higher percentiles.

Low-income households often depend on climate-sensitive livelihoods, such as informal labor or agriculture, which makes them prone to income loss from reduced work opportunities, damaged infrastructure, or crop losses. Limited access to savings, insurance, or alternative income streams restricts their ability to mitigate these effects. They also lack the resources to invest in protective measures such as flood barriers, resilient housing, or electric generators during power outages, further amplifying the impact of rainfall shocks on their daily lives [26,29,34].

To understand the causal mechanism through which the distance to the poverty line is affected, we estimate the impact of rainfall shocks on per capita *household income*, using Equation (2). We report the results in Table 3. Columns 1 to 5 exclude control variables, while Columns 6 to 10 include them. Columns 1 and 6 show the impact on the entire urban area, while the remaining columns focus on the different percentiles.

The results reveal that weather extremes cause a per capita household income drop, with worse consequences for poor households. While in urban areas, rainfall shocks reduce income by 3 % (Column 6), the 10th percentile experiences a 26 % reduction in income (Column 7), approximately 8 times greater than the effect observed in the overall urban area. This result illustrates the relationship between rainfall shocks, income, and the observed outcomes in poverty, providing empirical evidence that income serves as a key mechanism linking climate shocks to poverty dynamics.

Table 3
Effect of rainfall shocks on per capita household income (in logarithms).

	Urban Area (1)	Per10	Per25	Per50	Per75	Urban Area (6)	Per10	Per25	Per50	Per75
		(2)	(3)	(4)	(5)		(7)	(8)	(9)	(10)
Rainfall shock	−0.0334***	−0.254***	−0.145***	−0.0639***	−0.0414***	−0.0311***	−0.262***	−0.148***	−0.0631***	−0.0408***
	(-3.06)	(-2.65)	(-3.86)	(-3.07)	(-3.15)	(-2.88)	(-2.77)	(-3.96)	(-3.04)	(-3.12)
Control variables	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285478	16968	50866	118134	196525	285446	16964	50856	118115	196501
Adjusted R-squared	0.01	0.031	0.008	0.01	0.01	0.03	0.034	0.011	0.014	0.022

t statistics in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The complete table with the results of the control variables is found in Table A4 in the Appendix.

Table 4
Effect of rainfall shocks on the distance to the poverty line: highly susceptible and non-susceptible areas.

	Highly suscp.	Per10	Per25	Per50	Per75	Non-suscp.	Per10	Per25	Per50	Per75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rainfall shock	0.0046	−0.153***	−0.130***	−0.0761***	−0.0806***	0.144	−0.0617	−0.0219	0.0171	0.026
	(0.07)	(-3.51)	(-3.94)	(-2.85)	(-3.01)	(1.07)	(-1.51)	(-0.90)	(0.66)	(0.95)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	152609	8182	26731	64449	107438	130052	8262	22916	51686	86592
Adjusted R-squared	0.01	0.062	0.023	0.016	0.021	0.007	0.075	0.014	0.011	0.018

t statistics in parentheses.
***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1.
The complete table with the results of the control variables is in the Appendix, in Table A5 (Highly susceptible areas) and Table A6 (Non-susceptible areas).

Table 5
Effect of rainfall shocks on the distance to the poverty line: women and men.

	Women	Per10	Per25	Per50	Per75	Men	Per10	Per25	Per50	Per75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rainfall shock	0.0783	−0.140***	−0.0783**	−0.052	−0.0379	0.0865	−0.0631*	−0.0745***	−0.036*	−0.0246
	(0.87)	(-2.63)	(-2.36)	(-1.58)	(-1.16)	(1.00)	(-1.83)	(-3.03)	(-1.69)	(-1.12)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83048	5747	16209	36453	59394	202398	11217	34647	81662	137107
Adjusted R-squared	0.012	0.104	0.03	0.016	0.021	0.007	0.034	0.015	0.012	0.02

t statistics in parentheses.
***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1.
The complete table with the results of the control variables is in the Appendix, in Table A7 (Women) and Table A8 (Men).

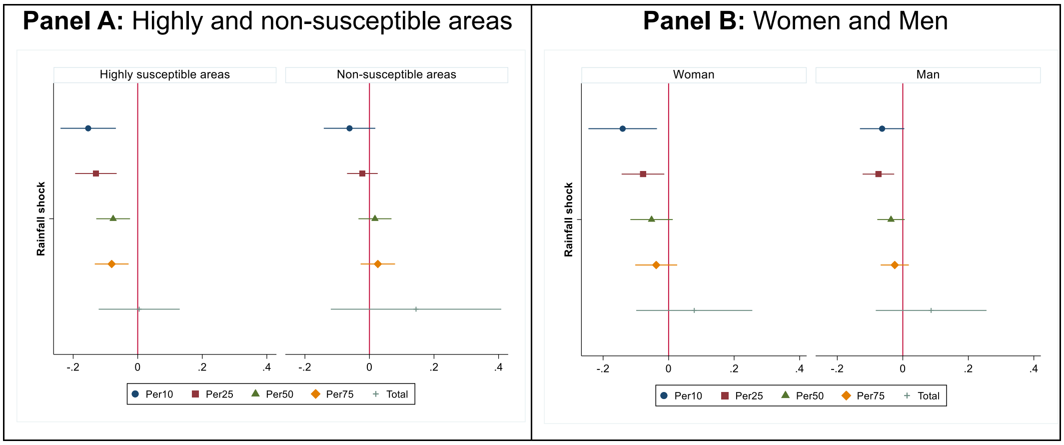

Fig. 7. Effect of rainfall shocks on the distance to the poverty line: subsample analysis.

To identify heterogeneous effects, we use the model of Equation (2) and analyze different subsamples. The results in the different percentiles are presented in Tables 4 and 5. Table 4 shows the impact on highly susceptible (Columns 1–5) and non-susceptible areas (Columns 6–10), and Table 5 presents results for women (Columns 1–5) and men (Columns 6–10).

In highly susceptible areas, rainfall shocks negatively and significantly affect the distance to the poverty line across all the percentiles but have a more pronounced effect on the lowest ones. For instance, households in the 10th percentile that face a shock move away from the poverty line by −15 percentage points (Column 2). At the 75th percentile, the distance to the poverty line moves by −8 percentage points (Column 5). These results highlight the vulnerability of all households in highly susceptible territories, where rain-related events not only directly threaten physical security but also exacerbate poverty conditions, disproportionately impacting the poorest.

Conversely, in areas without inherent susceptibility to natural hazards (columns 6–10), the impact of rainfall shocks on the distance to the poverty line is negligible or insignificant. However, it is worth noting that the coefficient value shows a bigger negative effect for the lower percentiles (Table 4 and Fig. 7, Panel A).

Low-income families living in highly susceptible areas often lack access to adequate infrastructure, which includes poor drainage systems, unpaved roads, and homes or businesses built with low-quality materials. Such conditions, along with their economic limitations, amplify their vulnerability to weather extremes [26,29,34]. These insights underscore the importance of considering location and geographic exposure to natural hazards when designing adaptation and mitigation strategies for weather shocks. They also highlight the need to prioritize highly susceptible areas where the most vulnerable households are concentrated.

The women and men analysis concludes that women in the lowest percentiles experience a severe impact. Rainfall shocks push women in the 10th percentile approximately −14 percentage points further from the poverty line (Column 2). This contrasts with the non-significant effect in the 50 and 75 percentiles (Columns 4 and 5). Men in the lowest percentile are also affected by −6 percentage points (Column 7), but less severely than women. However, these men experience greater consequences than women in high percentiles (Column 5). The results can be seen graphically in Fig. 7, Panel B.

The average distance to the poverty line for women in the 10th percentile is −52 %. Rainfall shocks increase this value by −14 percentage points, pushing them to −66 %, in a worse economic condition after a shock. Low-income women typically have lower levels of education and primarily engage in informal work (ENEMDU Panels, 2007–2019), an economic activity particularly vulnerable to climate shocks in urban areas [49]. Furthermore, they lack access to financial resources such as savings, insurance, or credit, which could help mitigate the impact of these shocks [49,50].

5. Conclusion and discussion

Urban poverty in Latin America extends beyond income deprivation. High levels of labor informality and spatial segregation in informal settlements further deepen social exclusion [5]. These overlapping disadvantages create compounded vulnerabilities, worsening the consequences of extreme weather events.

A key contribution of this study is to identify the causal effect of rainfall shocks, integrating multiple datasets such as panel household data, weather records, and geographic information on environmental hazards. This comprehensive approach allows us to capture dimensions that not only heighten individuals' vulnerability to weather shocks but also intensify their consequences. For example, the compounded vulnerabilities that arise from the intersection of poverty with being a woman or residence in highly susceptible areas.

The results show that while the poorest households are the most affected and experience an average decline of −9.8 percentage points in their economic well-being following rainfall shocks, the impact is significantly more severe for the poorest women and poorest individuals living in highly susceptible areas, reaching −14 and −15.3 percentage points, respectively. This underscores how structural disadvantages amplify climate vulnerability. Moreover, by incorporating geographic susceptibility data, we also reveal that even relatively wealthier groups within highly susceptible zones are not immune to these effects. In highly susceptible areas, households in the 75th income percentile face an −8.06 percentage points decline. Additionally, in non-susceptible territories, the consequences of rainfall shocks are not statistically significant, even for the poorest groups. These insights highlight the importance of integrating exposure to natural hazards or sex-disaggregated data into climate impact assessments, offering a more nuanced understanding of how environmental and socioeconomic factors interact to shape households' ability to withstand extreme weather events.

Just as all income groups are affected in highly susceptible areas, very extreme conditions also have consequences for all economic groups. In 2017—a highly atypical year characterized by exceptionally intense rainfall and devastating outcomes-rainfall affected approximately 150,000 people, compared to 10,000 in 2018. In Guayaquil, the average accumulated rainfall from January to May typically reaches 62.6 mm, but in 2017, it soared to 1,808.2 mm—nearly 30 times higher than usual [51,52]. Such extreme conditions have widespread repercussions, impacting both poorer and wealthier populations.[2] While low-income groups suffer the most, wealthier households are not immune to the effects of these unprecedented climate events. However, the key distinction lies in resilience and recovery capacity. Poor households often lack savings, social security, and insurance [49,50], making it nearly impossible for them to recover from such shocks. As a result, although extreme weather events affect all socioeconomic groups, they become poverty traps for the most vulnerable [53], due to structural disadvantages that prevent them from escaping poverty after being severely impacted.

Research on income, poverty, or consumption shows similar results to those presented in this study, indicating that extreme weather events worsen urban living conditions. In Mexico, Bolivia, and Peru, floods, droughts, or natural disasters have increased household and territorial poverty [11,54]. In the Philippines, household income declines following rainfall shocks, pushing more families into poverty [13]. In Guatemala and Uganda, weather extremes drive a −12.6 % and −17 % drop in urban household consumption [23,24]. As our study also points out, the economic impact of climate shocks is particularly harsh on low-income families, who are usually more exposed to floods than the average urban population [7,10]. Extreme events lower the chance of poverty escape [7,10].

Most governments in developing countries pay little attention to the urban poor in their policies and investments, especially regarding climate change and natural disasters [49]. Rainfall shocks negatively affect urban areas, with poor households, women, and people living in highly susceptible areas being the most affected. This highlights the importance of developing territorially targeted and sex-sensitive policies, as well as reinforcing social protection schemes for vulnerable populations. Given that poor families are

[2] Table A9 in the Appendix shows the regression analysis considering 2016–2017, as Ecuador experienced exceptionally extreme rainfall events in 2017.

more affected, these strategies should, where possible, incorporate the dimensions of urban poverty, such as inadequate infrastructure, labor informality, and spatial segregation.

Territorially, policies should prioritize urban areas where high poverty levels intersect with high exposure to natural hazards. In these zones, the development of climate-resilient infrastructure is important—, including the construction or enhancement of drainage systems, flood barriers, slope reinforcements, and retaining walls to stabilize landslide-prone zones. Relocation programs should consider affordable housing in less-susceptible areas, ensuring access to essential services and employment opportunities. These strategies not only increase resilience to extreme weather events but also address inadequate infrastructure, a defining characteristic of urban poverty.

Policies must also aim to reduce the high rate of labor informality among women, particularly those living in areas highly susceptible to natural hazards. To this end, technical training and skills development programs tailored to market needs can be implemented to support women's access to formal and more stable employment.

Social protection schemes that integrate disadvantaged groups should also be strengthened. For instance, the government can map households benefiting from the Human Development Bonus—a conditional cash transfer program in Ecuador—to identify those in areas highly susceptible to natural hazards. For residents in these zones, immediate access to emergency cash transfers or low-interest credit should be facilitated to support recovery from extreme weather events. Moreover, these social protection systems should be expanded to ensure that poor households in highly susceptible areas are effectively covered. Government assistance must be timely and effective, as a single income shock can force households to sell assets rapidly—often at low prices—leading to long-term consequences that entrench poverty.

In terms of urban planning, in highly susceptible areas, it is important to enforce realistic land use and building regulations. Safe land should be identified for low-income populations, and existing informal settlements should be upgraded whenever possible. At the community level, participatory workshops in informal neighborhoods can help integrate risk reduction into urban planning and strengthen ties between local authorities and residents. Local governments could be technically and financially strengthened to effectively lead locally grounded strategies in response to extreme weather events. This includes providing continuous training, ensuring better access to climate financing, and fostering stronger inter-institutional coordination.

Overall, poor households, women, and families living in highly susceptible areas must be actively included in public policy decision-making processes to ensure their needs are understood and effectively addressed. These policy recommendations underscore the importance of cross-referencing poverty maps with environmental hazards, weather shocks, and socioeconomic data to better guide investments and public policy.

CRediT authorship contribution statement

María Cristhina Llerena Pinto: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alisher Mirzabaev:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization.

Data availability statement

The data supporting the findings of this study come from the ENEMDU surveys and the Climate Hazards Center at the University of California, Santa Barbara (CHIRPS), which are accessible at https://www.ecuadorencifras.gob.ec/matrices-de-transicion-laboral/and, https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_daily/netcdf/p05/respectively. However, geographic information comes from the Geoinformation generation project and the Threat analysis against mass movements in Ecuador, which requires permission from the Secretary of Risk Management *[Secretaria de Gestion de Riesgos]* to be used. This data could be available upon request and with the Secretary permission https://www.gestionderiesgos.gob.ec/informacion-publica-del-servicio-nacional-de-gestion-de-riesgos-y-emergencias-modalidad-no-presencial/.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Annual panels (number of observations at the household level), ENEMDU Panels 2007–2019

Panels	Period	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Panel 1	Q3 (2007–2008)	3,920	3,928	0	0	0	0	0	0	0	0	0	0	0	**7,848**
Panel 2	Q4 (2007–2008)	3,886	3,907	0	0	0	0	0	0	0	0	0	0	0	**7,793**
Panel 3	Q1 (2008–2009)	0	3,973	3,999	0	0	0	0	0	0	0	0	0	0	**7,972**
Panel 4	Q2 (2008–2009)	0	3,916	3,906	0	0	0	0	0	0	0	0	0	0	**7,822**
Panel 5	Q3 (2009–2010)	0	0	4,078	4,102	0	0	0	0	0	0	0	0	0	**8,180**
Panel 6	Q4 (2009–2010)	0	0	3,829	3,862	0	0	0	0	0	0	0	0	0	**7,691**
Panel 7	Q1 (2010–2011)	0	0	0	3,752	3,746	0	0	0	0	0	0	0	0	**7,498**
Panel 8	Q2 (2010–2011)	0	0	0	3,903	3,930	0	0	0	0	0	0	0	0	**7,833**
Panel 9	Q4 (2011–2012)	0	0	0	0	3,205	3,180	0	0	0	0	0	0	0	**6,385**
Panel 10	Q1 (2012–2013)	0	0	0	0	0	3,554	3,552	0	0	0	0	0	0	**7,106**
Panel 11	Q2 (2012–2013)	0	0	0	0	0	4,175	4,151	0	0	0	0	0	0	**8,326**
Panel 12	Q3 (2013–2014)	0	0	0	0	0	0	1,320	1,349	0	0	0	0	0	**2,669**
Panel 13	Q4 (2013–2014)	0	0	0	0	0	0	5,663	5,675	0	0	0	0	0	**11,338**
Panel 14	Q1 (2014–2015)	0	0	0	0	0	0	0	6,852	6,853	0	0	0	0	**13,705**
Panel 15	Q2 (2014–2015)	0	0	0	0	0	0	0	13,032	13,014	0	0	0	0	**26,046**
Panel 16	Q3 (2014–2015)	0	0	0	0	0	0	0	3,827	3,827	0	0	0	0	**7,654**
Panel 17	Q3 (2015–2016)	0	0	0	0	0	0	0	0	3,723	3,716	0	0	0	**7,439**
Panel 18	Q4 (2015–2016)	0	0	0	0	0	0	0	0	13,717	13,784	0	0	0	**27,501**
Panel 19	Q1 (2016–2017)	0	0	0	0	0	0	0	0	0	7,792	7,805	0	0	**15,597**
Panel 20	Q2 (2016–2017)	0	0	0	0	0	0	0	0	0	7,854	7,844	0	0	**15,698**
Panel 21	Q3 (2016–2017)	0	0	0	0	0	0	0	0	0	3,644	3,677	0	0	**7,321**
Panel 22	Q1 (2018–2019)	0	0	0	0	0	0	0	0	0	0	0	7,713	7,681	**15,394**
Panel 23	Q2 (2018–2019)	0	0	0	0	0	0	0	0	0	0	0	8,334	8,323	**16,657**
Panel 24	Q3 (2018–2019)	0	0	0	0	0	0	0	0	0	0	0	8,417	8,413	**16,830**
Panel 25	Q4 (2018–2019)	0	0	0	0	0	0	0	0	0	0	0	8,594	8,581	**17,175**
Total		**7,806**	**15,724**	**15,812**	**15,619**	**10,881**	**10,909**	**14,686**	**30,735**	**41,134**	**36,790**	**19,326**	**33,058**	**32,998**	**285,478**

Table A2
Robustness tests

Model	Joint F test - Time-fixed effects		Wald test – Heteroskedasticity		Hausman test	
	F (*)	Prob > F	Chi2 (*)	Prob > Chi2	Chi2 (*)	Prob > Chi2
Distance to the poverty line (total urban area)	3.32	0.0000	1.8E+43	0.0000	3858.99	0.0000
Women	2.35	0.0002	7.1E+43	0.0000	7136.71	0.0000
Men	2.29	0.0002	1.8E+42	0.0000	1759.58	0.0000
Highly susceptible territories	2.23	0.0004	1.0E+42	0.0000	1787.54	0.0000
Non-susceptible territories	2.96	0.0000	2.2E+42	0.0000	2006.64	0.0000

Table A3
Effect of rainfall shocks on the distance to the poverty line

	Urban Area (1)	Per10 (2)	Per25 (3)	Per50 (4)	Per75 (5)	Urban Area (6)	Per10 (7)	Per25 (8)	Per50 (9)	Per75 (10)
Rainfall shock	**0.077**	**−0.0953*****	**−0.0705*****	**−0.0385****	**−0.029**	**0.084**	**−0.0980*****	**−0.0725*****	**−0.0376****	**−0.03**
	(1.19)	(-3.19)	(-3.58)	(-2.19)	(-1.61)	(1.3)	(-3.34)	(-3.69)	(-2.14)	(-1.57)
Education head of Household						0.0457***	0.00238	0.00315	0.00158	0.00783***
						(6.9)	(0.93)	(1.64)	(0.88)	(3.77)
Age head of Household						0.00459*	0.00246	0.00107	0.0007	0.00141
						(1.88)	(1.87)	(1.25)	(0.91)	(1.6)
Number of people in the Household						−0.231***	−0.0002	0.00949*	−0.0021	−0.0330***
						(-15.77)	(-0.04)	(2.44)	(-0.58)	(-7.02)
Number of children under 5 years						−0.191***	−0.0088	−0.0356***	−0.0749***	−0.152***
						(-6.32)	(-0.76)	(-4.35)	(-9.01)	(-15.57)
Number of older adults (over 65)						−0.254***	−0.0253	−0.0219	−0.0157	−0.0713***
						(-6.03)	(-1.22)	(-1.30)	(-1.02)	(-4.07)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(*continued on next page*)

Table A3 (*continued*)

	Urban Area (1)	Per10 (2)	Per25 (3)	Per50 (4)	Per75 (5)	Urban Area (6)	Per10 (7)	Per25 (8)	Per50 (9)	Per75 (10)
Observations	285478	16968	50866	118134	196525	285446	16964	50856	118115	196501
Adjusted R-squared	0.001	0.036	0.01	0.006	0.004	0.008	0.04	0.013	0.012	0.019

t statistics in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A4
Effect of rainfall shocks on per capita *household income (in logarithms)*

	Urban Area (1)	Per10 (2)	Per25 (3)	Per50 (4)	Per75 (5)	Urban Area (6)	Per10 (7)	Per25 (8)	Per50 (9)	Per75 (10)
Rainfall shock	**−0.0334*****	**−0.254*****	**−0.145*****	**−0.0639*****	**−0.0414*****	**−0.0311*****	**−0.262*****	**−0.148*****	**−0.0631*****	**−0.0408*****
	(-3.06)	(-2.65)	(-3.86)	(-3.07)	(-3.15)	(-2.88)	(-2.77)	(-3.96)	(-3.04)	(-3.12)
Education head of Household						0.0105***	0.00595	0.00558*	0.00168	0.00478***
						(8.3)	(0.81)	(1.74)	(0.86)	(3.33)
Age head of Household						0.00102*	0.00746**	0.00238	0.000996	0.000845
						(1.76)	(2.11)	(1.63)	(1.15)	(1.34)
Number of people in the Household						−0.0499***	−0.0129	0.0138**	−0.000848	−0.0172***
						(-16.19)	(-0.84)	(2.1)	(-0.21)	(-5.18)
Number of children under 5 years						−0.102***	−0.00197	−0.0539***	−0.0718***	−0.102***
						(-14.63)	(-0.05)	(-3.81)	(-7.74)	(-13.98)
Number of older adults (over 65)						−0.0635***	−0.0454	−0.026	−0.0169	−0.0419***
						(-6.61)	(-0.82)	(-0.91)	(-0.96)	(-3.46)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285478	16968	50866	118134	196525	285446	16964	50856	118115	196501
Adjusted R-squared	0.01	0.031	0.008	0.01	0.01	0.03	0.034	0.011	0.014	0.022

t statistics in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A5
Effect of rainfall shocks on the distance to the poverty line: Highly susceptible areas

	Highly suscp (1)	Per10 (2)	Per25 (3)	Per50 (4)	Per75 (5)	Highly suscp (6)	Per10 (7)	Per25 (8)	Per50 (9)	Per75 (10)
Rainfall shock	**0.00767**	**−0.144*****	**−0.126*****	**−0.0762*****	**−0.0791*****	**0.0046**	**−0.153*****	**−0.130*****	**−0.0761*****	**−0.0806*****
	(0.12)	(-3.20)	(-3.82)	(-2.86)	(-2.96)	(0.07)	(-3.51)	(-3.94)	(-2.85)	(-3.01)
Education head of household						0.0430***	0.00455	0.00302	0.00279	0.00681*
						(4.71)	(1.26)	(1.14)	(1.16)	(2.48)
Age head of household						0.000988	0.00318	0.00165	0.000688	0.000342
						(0.31)	(1.71)	(1.31)	(0.64)	(0.29)
Number of people in the household						−0.232***	0.00913	0.0118*	0.0000365	−0.0347***
						(-13.52)	(1.59)	(2.21)	(0.01)	(-5.48)
Number of children under 5 years old						−0.172***	−0.0163	−0.0392***	−0.0788***	−0.151***
						(-4.83)	(-1.03)	(-3.63)	(-7.63)	(-12.02)
Number of older adults (over 65)						−0.269***	−0.03	−0.0365	−0.00819	−0.0637**
						(-4.47)	(-0.78)	(-1.41)	(-0.37)	(-2.67)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	152627	8183	26737	64461	107452	152609	8182	26731	64449	107438
Adjusted R-squared	0.001	0.053	0.018	0.01	0.005	0.01	0.062	0.023	0.016	0.021

t statistics in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A6
Effect of rainfall shocks on the distance to the poverty line: Non-susceptible areas

	Non-suscp	Per10	Per25	Per50	Per75	Non-suscp	Per10	Per25	Per50	Per75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rainfall shock	**0.139**	**−0.063**	**−0.0221**	**0.0157**	**0.0266**	**0.144**	**−0.0617**	**−0.0219**	**0.0171**	**0.026**
	(1.03)	(-1.51)	(-0.90)	(0.6)	(0.96)	(1.07)	(-1.51)	(-0.90)	(0.66)	(0.95)
Education head of household						0.0504***	0.00228	0.00378	0.00102	0.0106**
						(5.05)	(0.65)	(1.33)	(0.37)	(3.21)
Age head of household						0.00911*	0.00242	0.0012	0.00128	0.00352*
						(2.37)	(1.28)	(1.07)	(1.11)	(2.53)
Number of people in the household						−0.238***	−0.0143*	0.0048	−0.00601	−0.0306***
						(-8.85)	(-2.22)	(0.82)	(-1.04)	(-4.15)
Number of children under 5 years old						−0.230***	0.00971	−0.0289*	−0.0682***	−0.157***
						(-4.28)	(0.64)	(-2.25)	(-4.72)	(-9.81)
Number of older adults (over 65)						−0.237***	−0.00256	−0.00919	−0.0257	−0.0808**
						(-3.96)	(-0.11)	(-0.42)	(-1.19)	(-3.06)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130066	8265	22920	51693	86602	130052	8262	22916	51686	86592
Adjusted R-squared	0.002	0.066	0.012	0.006	0.005	0.007	0.075	0.014	0.011	0.018

t statistics in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A7
Effect of rainfall shocks on the distance to the poverty line: Women

	Women	Per10	Per25	Per50	Per75	Women	Per10	Per25	Per50	Per75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rainfall shock	**0.0826**	**−0.138*** **	**−0.0743** **	**−0.052**	**−0.0379**	**0.0783**	**−0.140*** **	**−0.0783** **	**−0.052**	**−0.0379**
	(0.9)	(-2.60)	(-2.22)	(-1.58)	(-1.15)	(0.87)	(-2.63)	(-2.36)	(-1.58)	(-1.16)
Education head of household						0.0376***	0.00444	0.00187	0.00302	0.00852*
						(3.83)	(0.92)	(0.45)	(0.86)	(2.12)
Age head of Household						0.000499	0.00241	0.00317	0.00308	0.00157
						(0.1)	(1)	(1.8)	(1.84)	(0.81)
Number of people in the household						−0.173***	−0.00472	0.0125	−0.00134	−0.0218**
						(-7.88)	(-0.63)	(1.9)	(-0.21)	(-2.61)
Number of children under 5 years old						−0.202***	−0.00842	−0.0413*	−0.0786***	−0.181***
						(-3.29)	(-0.45)	(-2.57)	(-5.18)	(-10.07)
Number of older adults (over 65)						−0.394***	−0.00033	−0.0414	−0.0203	−0.118***
						(-4.69)	(-0.01)	(-1.11)	(-0.62)	(-3.63)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83058	5748	16213	36460	59402	83048	5747	16209	36453	59394
Adjusted R-squared	0.002	0.099	0.024	0.009	0.004	0.012	0.104	0.03	0.016	0.021

t statistics in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table A8
Effect of rainfall shocks on the distance to the poverty line: Men

	Men	Per10	Per25	Per50	Per75	Men	Per10	Per25	Per50	Per75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rainfall shock	**0.0769**	**−0.064***	**−0.0730*****	**−0.0375***	**−0.0263**	**0.0865**	**−0.0631***	**−0.0745*****	**−0.036***	**−0.0246**
	(0.89)	(-1.84)	(-2.97)	(-1.75)	(-1.19)	(1.00)	(-1.83)	(-3.03)	(-1.69)	(-1.12)
Education head of						0.0467***	0.00251	0.00202	0.00166	0.00650*
household						(4.53)	(0.78)	(0.83)	(0.72)	(2.34)
Age head of						0.00753	0.000687	0.000227	−0.000243	0.000707
household						(1.51)	(0.25)	(0.16)	(-0.18)	(0.47)
Number of people						−0.270***	0.00112	0.00861	−0.00698	−0.0442***
in the household						(-13.14)	(0.18)	(1.71)	(-1.47)	(-7.28)
Number of children						−0.181***	−0.00792	−0.0381***	−0.0670***	−0.133***
under 5 years old						(-4.85)	(-0.55)	(-3.87)	(-6.37)	(-11.08)
Number of older						−0.230***	−0.0275	−0.0195	−0.0117	−0.0539*
adults (over 65)						(-4.26)	(-1.02)	(-0.97)	(-0.63)	(-2.41)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	202420	11220	34653	81674	137123	202398	11217	34647	81662	137107
Adjusted R-squared	0.001	0.032	0.012	0.007	0.005	0.007	0.034	0.015	0.012	0.02

t statistics in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A9
Effect of rainfall shocks on the distance to the poverty line, **Panels 2016–2017**

	Urban Area (1)	Per10	Per25	Per50	Per75	Urban Area (6)	Per10	Per25	Per50	Per75
		(2)	(3)	(4)	(5)		(7)	(8)	(9)	(10)
Rainfall shock	**0.107**	**−0.0838***	**−0.0661****	**−0.0711****	**−0.0787****	**0.109**	**−0.0942****	**−0.0664****	**−0.0720****	**−0.0807*****
	(1.08)	(-2.41)	(-2.91)	(-3.18)	(-3.27)	(1.11)	(-2.65)	(-2.92)	(-3.22)	(-3.38)
Control Variables	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56116	2977	8791	21616	37301	56112	2977	8790	21613	37298
Adjusted R-squared	0.001	0.047	0.029	0.014	0.006	0.012	0.111	0.039	0.018	0.024

t statistics in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Data availability

The authors do not have permission to share data.

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