Coping with the Storm: Extreme Rainfall and Rural Land abandonment in Colombia

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Coping with the Storm: Extreme Rainfall and Rural Land Abandonment in Colombia.*

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Abstract

This paper examines how extreme rainfall shocks influence land-use decisions in rural Colombia. I combine satellite-based yearly land-use classification data with historical precipitation records and employ a difference-in-differences framework with multiple time periods to estimate the causal impact of extreme weather events. The results show that municipalities exposed to extreme rainfall experience a significant reduction in cropland share and a concurrent increase in bare ground area, consistent with land abandonment. These effects are more pronounced in municipalities with higher credit application rates, suggesting a coping strategy of migration and land abandonement. Furthermore, municipalities with a higher proportion of unproductive land experience larger losses in cropland, while those with more productive land tend to receive some migration by increase in built-up areas. These findings highlight the heterogeneous adaptive responses to weather shocks and their implications for rural land-use dynamics under extreme rainfalls.

JEL classification: Q15,Q54,Q24,O13,C23.

Keywords: Extreme rainfall, Land-use decision, Land abandonment, Adaptative responses, Climate adaptation.

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1 Introduction

Land-based economic activities such as agriculture, forestry, and grazing are fundamental to rural livelihoods, particularly in developing countries. At the same time, these sectors are major contributors to greenhouse gas (GHG) emissions, largely through land-use change and deforestation (Verma,Kamlesh et al., 2023). In Latin America and the Caribbean, agriculture and land-use change are the dominant sources of GHG emissions, driven in part by the expansion of agricultural frontiers (Brassiolo et al., 2023). Not only do these dynamics threaten ecosystems and biodiversity, but also expose rural populations to heightened environmental risks.

Climate change is amplifying the frequency and intensity of extreme weather events, including droughts and floods. Between 1970 and 2019, climate- and weather-related hazards accounted for roughly half of all recorded natural disasters and nearly three-quarters of economic losses worldwide (UN, 2021). Inadequate land and water management further compound these effects by degrading land productivity and increasing vulnerability to climate-related shocks (Dasgupta, 2021).

Colombia offers a compelling context to study the interaction between climate shocks and land-use decisions. Situated near the equator, the country does not experience conventional seasons but is highly exposed to irregular and intense precipitation patterns linked to El Niño-Southern Oscillation (ENSO)[1]. Nearly 98 percent of Colombian territory is rural, with pasturelands alone covering 30 percent of the national land area (DANE, 2015). Yet widespread environmental degradation, such as poor land control, water mismanagement, and advancing desertification (UNDDC & LND, 2018), has reduced the resilience of these ecosystems.

Land-use decisions in Colombia are shaped not only by market conditions and input prices but also by how farmers adapt to climate risk and uncertainty. Extreme rainfall may reduce the reliability of agricultural production, altering perceptions of land value and shifting the incentives for land use. In this paper, I ask: How do extreme rainfall shocks affect land-use decisions in Colombia?

A growing literature emphasizes that land value and yield are jointly determined by

[1]ENSO consists of two phases: "El Niño" and "La Niña," representing the warmer and colder phases, respectively.

biophysical, climatic, and socioeconomic factors (Mendelsohn, Nordhaus, & Shaw, 1994; Mendelsohn & Dinar, 2003; Schlenker, 2006; Kurukulasuriya & Mendelsohn, 2008; Huong, Bo, & Fahad, 2019). Weather shocks reduce the expected returns from land and may induce behavioral adjustments, particularly among risk-averse farmers whose welfare depends heavily on land income. These adjustments include shifts between crops, pastures, or forests, and —more critically— decisions to abandon land and migrate for better oppotunities.

I conceptualize land-use decisions as a form of investment under risk, where landholders allocate land to maximize expected returns while minimizing exposure to weather-related shocks. This framing suggests that extreme rainfall could prompt disinvestment in vulnerable land uses and greater reliance on coping mechanisms such as migration or financial credit (Desbureaux & Damania, 2018; Girard, Delacote, & Leblois, 2021).

To empirically estimate the causal effect of extreme rainfall on land use, I implement a difference-in-differences (DiD) framework with multiple time periods (Callaway & Sant'Anna, 2021), which allows for heterogeneous treatment timing and controls for both municipality and year fixed effects. This approach avoids known biases in two-way fixed effects (TWFE) estimators when treatment effects vary across groups or time (Goodman-Bacon, 2021).

I construct a panel dataset covering the period 2015-2022, combining high-resolution satellite imagery from Dynamic World (DW) for land-use pixel classification, historical precipitation data from Colombia's meteorological agency (IDEAM), and socioeconomic information from the 2014 Agricultural Census and Colombia's land reform information system (SIPRA). Land cover is classified into nine categories, from which I focus on trees, crops, and pastures as proxies for forest, agriculture, and livestock use, respectively. I define extreme rainfall shocks as deviations in annual precipitation exceeding two or more standard deviations above the historical municipal mean from 1970 to 1999 period.

The study finds that extreme rainfall events significantly impact land use, particularly in municipalities that experience atypical precipitation there is a signicative reduction of 0.92 percentage points in croplands. It is a reduction of 24.3 percentage of the crop-covered area on the municipalities where it represent aproximately 2.01 millions of ha, affecting food production and farmers' livehood. The overall effect, reveals that crop-covered areas decrease following extreme rainfall, with the most pronounced effects occurring between 2017-2018 and 2021-2022, with decreases in crop-covered area of 2.7 and 1.4 basis points, respectively. Additionally, while flooded vegetation temporarily increases in affected areas, no persistent average effect is observed. Conversely, bare ground expands notably in municipalities experiencing their first extreme rainfall in 2017, 2018, and 2022, suggesting a progressive shift where farmers initially reduce crop areas and siggenting progressive land abandondment, leading to increased bare land.

These results are robust across study examining the robustness of these effects at different precipitation intensities thresholds (1, 1.5, 2 and 2.5 standard deviations from the historical mean). At 1.5 and 2 standard deviations, there is a notable reduction in cropland while the is an increase in bare soil, reinforcing the hypothesis that extreme rainfall leads to land abandonment. However, the loss of statistical significance at higher thresholds suggests that fewer municipalities experience such extreme deviations, potentially limiting the precision of the estimates.

These results are robust across various rainfall thresholds (1.5 and 2 standard deviations for the historical mean) and are consistent with the hypothesis that extreme rainfall undermines land productivity, reducing cropland and inducing abandonment. Nevertheless, at higher thresholds (2.5 standard deviations), statistical precision declines due to fewer treated units.

Heterogeneity analyses reveal that municipalities with higher rates of farmer credit applications, larger shares of unproductive land, and lower land concentration are significantly more responsive to rainfall shocks. In contrast, areas with more productive land are more likely to increase built-up areas, potentially reflecting urbanization due to migration. Landowners with higher investment in land improvements show cropland reductions without corresponding increases in bare ground, suggesting better adaptive capacity. Conversely, those with lower investment levels show increased land degradation.

Finally, municipalities with larger national park areas show some evidence of pasture reduction, though parallel trends assumptions limit the interpretation of these results. Overall, the findings highlight how climate disturbances interacts with land productive reliability, financial access, and tenure conditions to shape rural adaptation or cope strategies and farmers' land-use decision-making.

Related literature

This paper contributes to the growing literature on climate adaptation by examining how extreme rainfall events influence farmers' land-use decisions. The underlying hypothesis is that land allocation across uses —such as crops, pastures,forestry or other uses— is an endogenous response to climatic shocks. Several studies emphasize the importance of accounting for endogenous land-use behavior when estimating the impact of climate on land values. For example, allowing for endogenous land use provides a better estimate of climate's effect on land value (Timmins, 2006).

More broadly, this work builds on studies showing that farmers adjust their crop choices based on climatic variation (Schlenker, 2006; Kurukulasuriya & Mendelsohn, 2008). Similar to crop-switching, farmers may reallocate land among different uses to maintain productivity under adverse weather conditions. This paper aims to identify behavioral patterns that reflect such shifts in land use—specifically, movements between cropland, pasture, forest, and other uses—as a form of adaptation to extreme rainfall.

Farmer responses to climate shocks vary significantly by local context, shaped by access to resources, credit, infrastructure, and information. Both short-term coping mechanisms and long-term adaptation strategies are influenced by institutional, cultural and environmental local conditions (Girard et al., 2021). However, recent evidence also highlights systematic biases in how farmers perceive rainfall patterns. Land-use history, such as prior conversion of pasture to cropland, can distort perceptions of whether conditions have become wetter or drier, potentially influencing subsequent decisions in maladaptive ways (Arora & Feng, 2024).

Climate-induced shifts in land use may also interact with broader socioeconomic outcomes, including migration. In settings with high climate vulnerability and limited irrigation infrastructure, rainfall shocks reduce agricultural yields and can lead to rural out-migration (Munshi, 2003; Mahajan & Yang, 2020; Velásquez, 2020; Hadzi-Vaskov & Beltran, 2023). This paper contributes to this literature by documenting behavioral adjustments in land use that may precede or accompany such responses.

Several empirical strategies have been developed to assess how land-use decisions respond to climate change. The Ricardian approach, for instance, estimates the effect of climate on land values using cross-sectional data (Mendelsohn et al., 1994; Mendelsohn

& Dinar, 2003; Timmins, 2006). Agricultural models have also been used to simulate future crop yields under alternative climate scenarios (Jägermeyr et al., 2021), while others examine how yield variability itself can induce crop-switching behavior (Schlenker, 2006). This study departs from these approaches by exploiting temporal and spatial variation in extreme rainfall events to analyze land-use shifts at high spatial resolution in a development country such as Colombia, a setting where climate shocks are recurrent and there are adaptation constraints.

The findings add to the understanding of climate resilience in rural areas, providing evidence that farmers reoptimize land use in response to weather extremes. By tracking year-on-year changes across municipalities, this paper highlights the dynamic nature of climate adaptation and the heterogeneous pathways through which households adjust to increasing climate risk.

The reamainder of the paper is structured as follows: Section 2 provides background on Colombia's climate exposure, land use, and land tenure. Section 3 describes the data sources and variable construction. Section 4 outlines the empirical strategy. Section 5 presents the main results, followed by a discussion in Section 6. Section 7 concludes.

2 Context: Colombia

This section provides more context on relevant features of Colombia to understand the country's climate and land use. I divide this section into two subsections. The first deals with Colombia's climatic characteristics, and the second with land use and land ownership throughout the country.

2.1 Climate patterns

Colombia has unique climatic characteristics. Located close to the equator, the country does not experience conventional seasons, but periods with different levels of precipitation. In addition, the influence of the Pacific Ocean, the Caribbean Sea, the Amazon rainforest and the three branches of the Andes Mountains contribute to the variability of climate cycles and weather patterns in the different hydrographic zones. Some regions, such as the Amazon, have more stable precipitation levels, while others, such as the Pacific region, experience high precipitation. In contrast, the Caribbean, Andean and Orinoquia regions alternate months of heavy rainfall with drier periods.

Colombia is also highly susceptible to El Niño-Southern Oscillation (ENSO) events, which strongly impact land and water use. The different La Niña phases between 2010-2020 led to over 400,000 animal deaths and forced the relocation of 6 million animals due to flooding. In 2010 alone, over 68,000 hectares of crops were affected by extreme weather, including floods and frost. On the other hand, El Niño brings drought, severely affecting water supplies for agriculture, livestock, and human consumption (Borja-Vega, de Groot, & Serrano, 2018). Moreover, Colombia faces increasing land degradation and desertification due to poor water and land management. This has led to river sedimentation and frequent flooding, further complicating sustainable land use practices. (ElTiempo, 2023).

In addition, Colombia has the highest frequency of extreme events in South America in with rapid population growth in the context of unplanned urban areas, informal settlements and densely populated coastal areas increasing the population's risk to extreme events. It is estimated that 84% of the population and 86% of the country's assets are located in areas exposed to two or more types of climate hazards. Furthermore, the country has a historical record of hazards in which floods and landslides are the main source of climate hazards, accounting for 64.11% of the total number of natural hazards occurring between 1980 and 2020 throughout the country (check figure A.1)(WB, 2021). In consequence, studing extreme rainfalls in Colombia is relevant due to their historical recurrence and the populaton that they could affect.

2.2 Land usage and ownership

In 2014, the National Administrative Department of Statistics (DANE) in Colombia conducted its third National Agricultural Census, the largest ever undertaken in the country. The goal was to gather detailed information about rural areas and rural population. The census focused on dispersed rural areas, regions without municipal centers nor concentrated populations, which account for 97.8% of the national territory (DANE, 2015). [2]

In terms of land use, the census registered that 38,6% of the territory is used for agricultural purposes, 56,5% are natural forest, 2,2% are not for agricultural use and 2% have other uses; where 80% of the land used for agricultural production is used in pastures, 19,3% in crops, and 0,3% in agricultural infrastructure. These figures highlight the predominance of agricultural land used for pastures, primarily for cattle raising, and the significant lack of infrastructure to support agricultural activities in rural areas.

In my empirical data described in section 3, I am able to measure in average 86.12% of the municipalities area in which 61% correspond to trees as an aproximation of natural forest. The agricultural area could be the sum of pastures and crops which sum up in average 20,4% of the municipalities area. In addition, my data shows that 19% of agricultural area are crops and 80% are pastures quite comparable as relation reported in the census.

In terms of property, DANE defines the unit of observation as a "Unit of Production" (UP), which may be either an agricultural production unit (UPA) or a non-agricultural production unit (UPNA). Each UP is managed by a single person, company, or association that assumes the risks and responsibilities of production. The census data reveal significant inequality in land ownership: approximately 76% of rural land is owned by only 0.4% of the UPs, each of which owns more than 500 hectares, but it is the small UPs with less than 5 hectares that collectively own only 2.3% of the land. Oxfam's measurement of a land Gini coefficient of 0.88 corroborates these findings[3], underscoring the extreme concentration of land ownership and decision-making power in Colombia. Additionally, I was found on census data that UPAs of more than 500 hectares represent on average 40.61% of the surveyed area in the municipalities.

Another characteristic on the land property comes from the land ownership of the ethnic groups in Colombia. Ethnic groups in Colombia have ownership rights over 35% of the country's land. Most of this land, 84.2%, is held by indigenous groups, followed by Afro-Colombian communities (15.7%) and ancestral root territories (0.01%). On aver-

[2] For more details, see the official DANE dashboard: https://www.dane.gov.co/files/CensoAgropecuario/entrega-definitiva/Boletin-1-Uso-del-suelo/1-Boletin.pdf.

[3] For more details Félix Posada Rojas wrote more about land concentration problem and explain the land GINI coefficient in his article https://cpt.org/2021/07/06/colombia-land-ownership-mother-all-conflicts

age, 90% of the land owned by these ethnic groups is covered by forests (DANE, 2015). These groups are well-known recognized for their cultural practices that prioritize forest conservation, as they have lived in these ecosystems for decades, and in the case of indigenous peoples, millennia. However, I find that the indigena's territories extent within the municipalities is on average just 5% of municipal area.

3 Data

This article aims to quantify the effects of environmental disturbances on land use decision making at the municipal level. It exploits spatial and temporal variations caused by extreme rainfall events, which influence farmers' coping strategies or coping practices in their land use decision making.

3.1 Satellite information

In my empirical application I use satellite information from Dynamic World (Brown et al., 2022). DW is a free to access Google product with information since the end of 2015 up to date. It is a machine learning model that classified the terrain of Sentinel2 images at 10x10m pixel resolution into nine different categories: water, trees, grass, crops, shrub & scrub, flooded vegetation, built-up area, bare ground and snow and ice. Trees, crops, and grass classification are going to be my measure of land use desicion-making between forestry, crops or pasture for cattle. However, I take into account water, shrub & scrub, flooded vegetation, built-up area and bare ground area to capture broader changes in farmers' land use behavior.

This approximation depends on the quality of the images and the cloud density at the time the satellite took the images. Therefore, to obtain the land use measure I count each month how many pixels the DW model classifies in each category for each municipality. Then, I select the month in which the model manages to classify the most area in the year for each municipality in order to extract the highest representation of the land distribution in the municipalities each year.

On the other hand, to minimize the noise generated by the missing area due to cloudy images and the extent of the area of the municipality, I calculate the proportion of land over the total classified area of the municipality. I have performed this process for each municipality.

$$PortionArea_{l,m} = \frac{Area_{l,m}^{DW}}{Area_{m}^{DW}}$$

Where $PortionArea_{l,m}$ represent the portion of land type l in municipality m, $Area_{l,m}^{DW}$ is the area of land l in municipality m classified by DW.

Table 1 shows the summary statististics for every type of land in the sencond panel, where each land type of interest is shown as the percentage it represents in the municipality. Here, it presents a similar relation in the agricultural area between pasture and crops as DANE's Agricultural Census. The agricultural area could be the sum of pastures and crops, in my data 19% of agricultural area are crops and 80% are pastures quite comparable as relation reported in the census (section 2.2), but with the adition that DW classification is able to capture yearly variation.

3.2 Precipitation information

For precipitation quantification, I use information provided by meteorological sensors from IDEAM which is the official institute provider of hydrological, meteorological, and environmental data in the country. I use disaggregated monthly raw data information by meteorological and hydric sensor that IDEAM provided to me. However, I aggregate the monthly data to annualize data since that is the frequency of my empirical design and I create an annual time series by sensor. I use 2,681 sensors which measure precipitation across the country (Figure A.2), the data covers the years 1970 through 2022.

My period of analysis spans from the last months of 2015 to 2022 because DW has started classifying land since the last months of 2015. In that period 1709 sensors were working in the country. The spatial distribution in Figure A.2 presents all available sensors used for the precipitation measures. I use the 2681 different sensors distribuited in 863

Table 1: Summary statistics

Panel A: Municipal Statistics	**Mean**	**SD**	**Min**	**Max**	**Count**
Municipality area(km^2)	1018.96	3227.43	6.89	65729.66	1110
PNN area(%)	12.70	19.59	0.00	100.00	1110
Resguardos area(%)	5.04	16.53	0.00	99.99	1110
Credit application	10.54	7.55	0.00	50.73	1110
No use of any land improvement (%)	42.96	19.03	7.07	94.85	1110
Water use dificulties because of a natural disaster(%)	1.68	3.28	0.00	46.15	1110
Large land ownership (%)	40.61	27.87	0.00	99.99	1110
Historic average precipitation(mm)	1499.47	1326.86	0.00	9231.42	1110
Historic std. deviation precipitation(mm)	414.51	421.25	0.00	4725.33	1110
Excelent to good productive land	6.40	12.18	0.00	84.80	1108
Moderate to mid-productive land	24.02	21.93	0.00	98.42	1108
Regular to unproductive land	57.05	29.17	0.00	100.00	1108
Flood-prone land	8.32	15.91	0.00	98.95	1108

Panel B: Panel Statistics	**Mean**	**SD**	**Min**	**Max**	**Count**
Area analyzed by DW (km^2)	718.85	2642.75	0.00	64479.85	8880
Total area analyzed(%)	71.25	29.74	0.00	100.00	8880
Trees area(%)	61.00	24.51	0.00	99.99	8880
Crops area(%)	3.70	9.24	0.00	87.53	8880
Grass area(%)	16.70	14.23	0.00	100.00	8880
Water area(%)	2.05	6.40	0.00	100.00	8880
Flooded vegetation area(%)	0.51	2.48	0.00	59.65	8880
Built area(%)	1.52	2.91	0.00	54.67	8880
Bare area(%)	0.64	2.18	0.00	48.24	8880
Average precipitation(mm)	1998.61	1247.99	0.00	13379.10	8880
Average precipitation weightened by subhydrographic zone(mm)	2002.51	1357.02	0.00	13252.87	8880

Panel C: Treatment	**Mean**	**SD**	**Min**	**Max**	**Count**
Atypic rain 2SD	0.06	0.24	0.00	1.00	8880
First extreme weather 2SD	487.61	864.34	0.00	2022.00	8880
since atypic rain 2SD	0.10	0.30	0.00	1.00	8880

Notes: In panel A, each observation corresponds to data at the municipal level. In panels B and C, each observation corresponds to data at the municipal-year level. The table presents the main variables, including their mean, standard deviation, minimum and maximum values, and the total number of observations. Panel A shows the principal municipal characteristics use in this text work. Land variables are reported in percentage of the total municipal area, while precipitation variables are presented in millimeters (mm). The weighted precipitation measure represents the historic mean precipitation (calculated from data prior to 2000) weighted by the mean precipitation recorded by sensors within each sub-hydrologic area, proportional to the total area of the municipality.

municipalities for historical precipitation measure from 1970-2000. Due to some sensors desactivation, only 1709 were active in my period of analysis between 2015 and 2022 distribuited 804 municipalities. I made a sensor triangulation to measure the precipitation on municipalities without their own sensor in the years 2015 to 2022. Then, I use the 1970-2000's mean and standard deviation as historic parameters to find the precipitation deviation of the historic mean in the period of analysis. The following equation shows the measure of deviation.

$$Deviation_{m,t} = \frac{\mu_{m,t} - \mu_{m,historic}}{\sigma_{m,historic}}$$

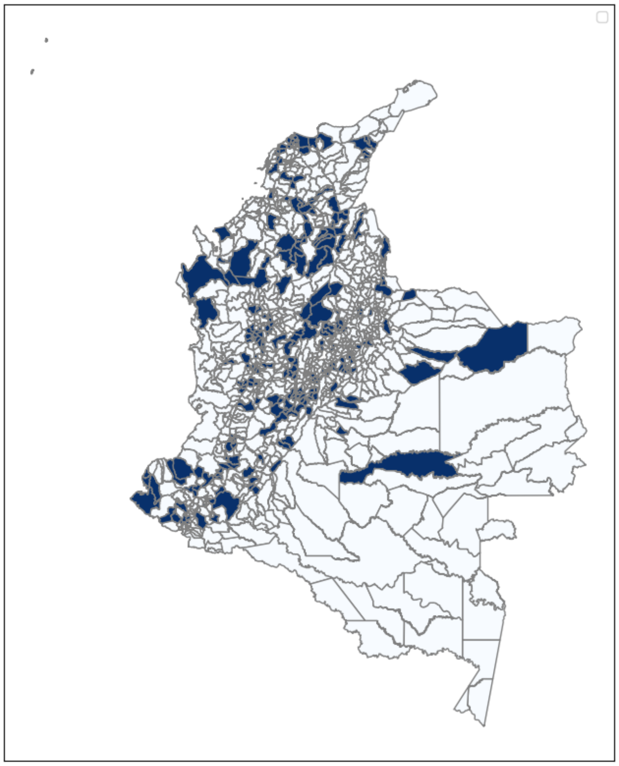
Where variable μ represents the average precipitation and its subindex m, t represents the municipality-time level, and $\mu_{m,historic}$ and $\sigma_{m,historic}$ represent historic mean and standard deviation within the municipalities, respectively. In addition, I measure a weighted precipitation taking into account the proportion of influence of all hydrrographic subzones that municipalities have given their topography and hydrographic characteristics. However, I do not find a significant difference between weighted approximation and unweighted mean. Therefore, I have used the mean and standard deviation without weights in my empirical approximation in order to measure the municipality deviation of the mean.

In table 1, I show in panel C my treatment variable that I generate it as a dummies variables to identify extreme weather events, defined as deviations from the historical mean greater than 2 standard deviations[4]. There are identifiers for the year in which the municipality experienced its first atypical precipitation, it defines its group, and the treatment assignment that corresponds to that year and subsequent years in which the municipality experienced its first extreme precipitation. However, historical data were missing for 258 municipalities. To address this, I identified the neighboring municipalities of those with missing data, calculated the average of the extreme weather dummy variables for these neighbors, and assigned the extreme rainfall dummy variable to the municipality in question only if the majority of its neighbors had a value of 1. Using this approach, I was able to impute missing data and obtain complete information for 1,110

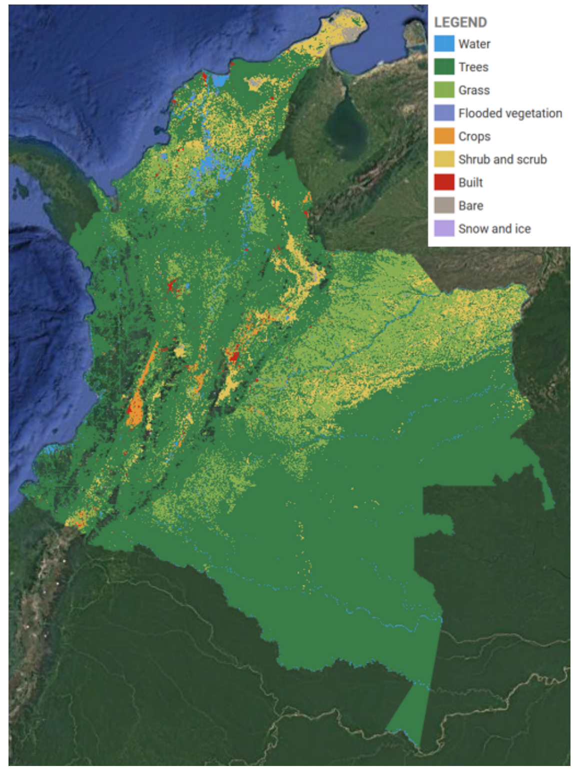
[4] As a robustness check, I show different assigment of deviation of the mean at 1, 1.5, 2 and 2.5 standard deviations from the historical mean in section 5.2.1, and their respective performance.

Figure 1: Treated municipalities and land classification map

(a) Ever treated municipalities



(b) Dynamic world classification



Notes: Figure 1a presents the geographical location of ever treated municipalities which experienced extreme rainfall show across the country. Figure 1b shows a picture of the mode land classification performed by Dynamic World on Colombia's territory between years 2017 to 2020.

municipalities.

3.3 Municipal characteristics

In order to analyze the different municipal characteristics I mainly use the National Agricultural Census published by DANE in 2014. It was the largest agricultural census conducted in the country and its objective was to collect detailed information on rural areas and rural population. The census focused on dispersed rural areas, regions without municipal capitals or concentrated population, which represent 97.8% of the national territory (DANE, 2015). Specifically, I extract information on behaviors and characteristics of UPAs such as credit application, use of land improvements and what type of land improvement [5]. All of them could be mutually applicable, with the exception of no land improvement, which excludes the rest. Particularly for the extension of the UPAs I categorized them based on the same groups that DANE describes in the descriptive results of the Census [6]. I measured the average of all these characteristics at the municipal level to extract the average characteristics and the behavior of each municipality for a more heterogeneous analysis (see Table 1, Panel A).

To further analyze the effects of extreme rainfall, I incorporate additional land and municipal characteristics. First, I use data from the Information System for Agrarian Reform (Sistema de Información para la Reforma Agraria, SIPRA) to measure land productivity based on Homogeneous Physical Units (Unidades Físicas Homogéneas, UFH). The UFH classification assigns land productivity values according to soil characteristics and market access, categorizing land into 13 distinct quality levels(UPRA & ANT, 2021). For this study, I aggregate these into three broader groups: high-productivity land, medium-productivity land, and low-productivity land[7]. I then compute the municipal-level share of each land quality category for heterogeneous effects analysis.

Additionally, I measure the share of indigenous resguardos and National Natural Parks within each municipality. These variables allow for further municipal-level heterogeneity analysis, providing deeper insights into the differential impacts of extreme rainfall.

4 Methodology

This study seeks to contribute to understanding the causal effect of extreme rainfall events on municipality-level aggregates of farmers' and peasants' land use decisions among crops, pasture, and forestry as a response to extreme weather. To achieve this, I employ a Difference-in-Differences (DiD) methodology with multiple time periods, following the framework of (Callaway & Sant'Anna, 2021). This DiD specification allows

[5] There are different types of improvement such as: organic fertilizer, chemical fertilizer, acid correction, land burning, prayers, rituals, ritual payments or no land improvement.

[6] DANE classified the extension of the UPAs as UPA with: less than 5ha, 5-10ha,10-50ha, 50-100ha, 100-500ha, 500-1000ha, and more than 1000ha.

[7] High-productivity land includes the top three UFH classifications (excellent to good), medium-productivity land encompasses moderate to average quality, and low-productivity land comprises regular to unproductive land.

for the absorption of location fixed effects and mean changes over time that impact all locations equally. I chose the Callaway & Sant'Anna specification over the traditional Two-Way Fixed Effects (TWFE) approach, as the latter is prone to a well-known bias when making invalid comparisons in the presence of variation in treatment timing (Goodman-Bacon, 2021).

The DiD methodology with a multiple time period treatment allows me to analyze the variation in timing of municipalities' first extreme rainfall events. This approach captures how municipalities adapt their land use following initial exposure to extreme rainfall, aiming to prepare for future events. Using this methodology, I extract the Average Treatment Effect on the Treated (ATT) for groups of municipalities classified by the year they experienced their first extreme rainfall and assess how the duration of exposure to this behavior changes impacts land use decisions regarding crops, pastures, or trees. The land use decision-making model I estimate is as follows:

$$PctArea_{l,m,t} = \alpha_m + \gamma_t + \beta^{CS} * Post_{m,t} + \epsilon_{m,t}$$

Where $PctArea_{l,m,t}$ represents the portion of land use for kind l, in municipality m in the period t. α_m is the municipality fixed effect coefficient, and γ_t is the year fixed effect estimator. β^{CS} is the Callaway & Sant'Anna (CS) estimator for multiple-period treatments, applied when $Post_{m,t}$ is active.

Here, $Post_{m,t}$ is equals to one (1) since the first time the municipality is exposed to an extreme rainfall. It happens when annual precipitation exceeds two historic standard deviations from the historic precipitation mean. Look that I assume that extreme variations in climate cause a change in the mindset of how farmers make decisions about the use of their land. The equation has been run separately for each type of land use. It means that, there are eight different results for every land classification[8].

This methodology is based on the assumption that from the first time the municipality is treated, it will be treated for the rest of the periods. Through this assumption this methodology allows me to understand the land behaviors in the municipality since its

[8]Types of land classification: crops, pastures, trees, water, flooded vegetation, shrub and scrub, built, and bare ground areas.

first extreme event occurs and the possible persistent changes or not in the land use decision making in the municipalities given that there are municipalities that experienced their first extreme event in different periods.

5 Results

I divide this section into two sub-sections. The first one investigates the effects of the extreme high rainfalls on the land use decision-making from farmers in Colombia. The second section analyzes heterogenity and discuss some robustness check over the estimation.

5.1 Land-use decision making consequences

The main result of this work is shown in Table 2, I show the group-time mean effect (Panel A) and the TWFE estimation (Panel B). The different columns represent the analysis on the different uses that farmers could give to their land, the ones that represent the principal agricultural productive activities are trees (column 1), pastures (column 2) and crops (column 3). Table 2 shows that there is a significant average reduction of 0.92 percentage points in the amount of crop-covered area while there is an increase in bare ground area of 0.24 percentage points in municipalities that suffered atypical rains.

In fact, this result suggests that farmers reduce crops on their land and abandon it, probably because it is susceptible to rainfall-related risk. It shows a reduction of 24.3% of the crops area on the municipalities where it represent aproximately 2.01 millions of ha, affecting food production and farmers' livehood. Parallel trends can be consulted in Figure A.3. Particularly for pastures and water covered areas, parallel trends assumption is not fullfilled.

Table 3 presents the group-time average treatment effects on land use. In addition to the overall group averages (GAverage), which correspond to the estimates reported in Table 2, the table also displays the effects of treatment participation for each group across all time periods following the first instance of atypical precipitation, which triggered be-

Table 2: Effect of atipic rainfall over land-use decision making

	Panel A: Group-time average treatment effects							
Dep. Variable:	Trees	Pasture	Crops	Water	Flooded Vegetation	Built	Bare	Shrub & scrub
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Atypic rain 2SD	-0.21	0.12	-0.92**	0.15	-0.00034	0.12	0.24***	0.45
	(0.86)	(0.61)	(0.43)	(0.17)	(0.16)	(0.21)	(0.094)	(0.64)
Municipalities treated	256	256	256	256	256	256	256	256
Municiplities always treated	12	12	12	12	12	12	12	12

	Panel B: Two-way Fixed Effects							
Dep. Variable:	Trees	Pasture	Crops	Water	Flooded Vegetation	Built	Bare	Shrub & scrub
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
since atypic rain 2SD	-0.24	0.17	-0.90**	0.60***	-0.023	0.11	0.19**	0.049
	(0.74)	(0.48)	(0.37)	(0.17)	(0.097)	(0.16)	(0.081)	(0.53)
Mean Dep.Var. Control	61.03	16.68	3.79	1.99	0.52	1.51	0.62	13.37
Treated Munis	268	268	268	268	268	268	268	268
Munis Analyzed	1110	1110	1110	1110	1110	1110	1110	1110
N. Obs	8880	8880	8880	8880	8880	8880	8880	8880
R^2	0.82	0.79	0.83	0.60	0.70	0.83	0.63	0.76

Notes: Each observation corresponds to the municipal-level data aggregated by year. Over the 268 treated municipalities there were 12 who were always treated, in order to extract the average effects those municipalities were not taken into account in the CS estimation since there is no way to measure its pre-treatment behaivor. Cluster errors by municipality. *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

havioral changes (G + first year of atypical rainfall). The GAverage represents the overall Average Treatment Effect on the Treated (ATT) across all groups, serving as a summary parameter that captures the weighted average effect of treatment participation. Specifically, it reflects the average impact experienced by municipalities that encountered atypical precipitation in any given period.

The results indicate significant reductions in crop covered areas for municipalities that began altering their behavior in response to extreme rainfall events. These changes are align with the precipitation peaks recorded between 2015 and 2022, as illustrated in Figure A.4. Notably, two peaks — between 2017-2018 and 2021-2022—were identified as having, in average, atypically high rainfall across the country.

Additionally, Table 3 presents significant effects on flooded vegetation for the year 2018 and 2021 that it is logical for the ecosystem to remain with a flooded zone for a while after experiencing heavy precipitation. Still, in average there is no effect for that type of terrain. On the other hand, bare ground has significant average effect in the groups that experience their first extreame rainfall in 2017, 2018 and 2022, most of the year in which high precipitation occurred in Colombia.

The disaggregation of the groups allows us to show that farmers first reduce the area covered by crops when faced with extreme rainfall and finally abandon it, leaving bare soil areas.

Table 3: Disaggregated group-time average treatment effects

Dep. Variable:	Trees	Pasture	Crops	Water	Flooded Vegetation	Built	Bare	Shrub & scrub	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
GAverage	-0.21	0.12	-0.92**	0.15	-0.00034	0.12	0.24***	0.45	256
	(0.86)	(0.61)	(0.43)	(0.17)	(0.16)	(0.21)	(0.094)	(0.64)	
G2016	1.04	-1.15	0.41	0.12	-0.041	-1.20	0.30*	-0.021	28
	(4.02)	(3.07)	(0.53)	(0.75)	(0.061)	(1.81)	(0.16)	(2.11)	
G2017	4.12*	-1.25	-2.72*	0.20	0.17	0.14	0.36***	0.030	50
	(2.49)	(1.51)	(1.63)	(0.41)	(0.22)	(0.19)	(0.13)	(2.12)	
G2018	-2.57	4.82***	-0.40	-0.040	0.21**	-0.081	0.26*	-2.27	11
	(1.69)	(1.72)	(0.40)	(0.18)	(0.11)	(0.089)	(0.15)	(1.64)	
G2019	4.89	-2.44	0.40	-0.11	0.016	-0.26	0.074	-2.91***	5
	(3.83)	(2.67)	(2.60)	(0.68)	(0.035)	(0.76)	(0.081)	(0.86)	
G2020	-2.59	-0.081	0.40	-0.15	-0.43	0.37	-0.29	2.73	14
	(2.24)	(2.49)	(0.57)	(0.20)	(0.43)	(0.25)	(0.33)	(3.18)	
G2021	-2.14*	0.69	-1.44*	0.35	0.47*	0.33**	0.056	1.55*	64
	(1.23)	(0.89)	(0.76)	(0.23)	(0.26)	(0.15)	(0.17)	(0.90)	
G2022	-1.34	0.49	-0.25	0.062	-0.40	0.39**	0.39*	0.19	84
	(1.29)	(0.91)	(0.57)	(0.32)	(0.37)	(0.17)	(0.23)	(0.89)	

Notes: This aggregation provides the average effect of participation in the treatment for observations in each group averaged across all time periods after that group becomes treated (Callaway, Sant'Anna, & Quispe, 2024). The length of exposure to treatment affects the average effect, and they are groups with different level of exposure. N represents the municipalities treated. Cluster errors by municipality. $^*p < 0.10$, $^{**}\ p < 0.05$, $^{***}p < 0.01$.

5.2 Robustness and Heterogenity

5.2.1 Robustness

Table A.1 presents the robustness of the regressions in which municipalities were assigned to an atypical precipitation by different precipitation intensities usign two-ways fixed effects. The assignment was 1, 1.5, 2 or 2.5 standard deviations from the historical mean, and each row and column represent a different regression, each one for each possible land use. All results have their separate estimation with the assigned treatment.

In addition, Table A.1 shows that at 1, 1.5, and 2 standard deviations there is statistical significance reduction for crop covered area. Although, for water are significant increment in all different specification of treatment. These results are not interesting, as they say that crop reduction was replaced by water.

Furthermore, Table A.2 shows the robustness of the regressions in which municipalities were assigned to an extreme precipitation by different precipitation intensities using Callaway & Sant' Anna methodology. Similarly to the previous analysis, the assignment was 1, 1.5, 2 or 2.5 standard deviations from the historical mean, and each row and column represent a different regression, each one for each type of land of interest: trees, pastures, and crops. All results have their separate estimation with the assigned treatment.

Table A.2 shows that for the 1.5 and 2 standard deviations specifications there is a statistically significant treatment effect on the reduction of the area covered by crops and the increase of bare soil. In addition, the table suggests a slight increment in water area at 1 and 1.5 standard deviation specification. The loss of significance is probably due to the fact that few municipalities have experienced these high levels of rainfall variation. Another important fact that emerges from the table is that a significant increase in bare soil area is only observed when there is a significant reduction in the area covered by crops.

In addition, the noise produced by the extreme drought episodes experienced by the municipalities during the analysis period could be of concern. In order to analyze changes in the estimate, the table A.3 shows the mean treatment effect results disaggregated by time group, similar to Table 3, but excluding municipalities that had ever experienced an extreme drought episode. This excludes a total of 178 municipalities, of which only 38 were treated in the main results, producing fairly similar results, somewhat small but consistent with the specification using all available municipalities.

5.2.2 Municipal characteristics heterogenity

Table 4 presents seven sources of heterogeneity: credit application, good land productivity, poor land productivity, land concentration, the use of land improvement practices by farmers, the area of indigenous' resguardos within the municipality, and the presence of National Nature Parks within the municipality. Regarding credit application, the heterogeneous results show that in the municipalities where farmers apply for more credit, a large reduction of 2.06 percentage points in the municipalities' cropland area is evident. This is more than double the effect shown in the general case (0.92). While there is an increase in non-cropped and urbanized areas, these could be signs of abandonment and migration to urban areas.

Respecting to characteristics of land productivity there are interesthing results. In terms of land, municipalities where the proportion of good land is above average do not behave as similarly compared to municipalities where the proportion of poorly productive land is above average. For both the resulst suggest a evidence of reduction in cropland of 2.31 and 1.46[9] percentage points, respectively. Nevertheless, the responses in other types of land is different. In the case of municipalities with good productive land, it suggest that those territores decrease the portion of cropland while increase portion of threes. It probably happend because in average the land with high productivity is scarce (it represents in average 6.4% of municipalities' surface area), and it should be necesarly to preserve, then they are likely to reduce cropland in less productive areas and plant trees instead to cope with extreme weather. Another interesting result is that in municipalities where unproductive land is below average there is a significant increase in built-up areas, another sign of migration in which farmers probably migrate in search of better opportunities in municipalities where land is at least slighly more productive.

In regard to land concentration, the results indicate that municipalities with land concentration below the mean experience a significantly larger reduction in cropland (1.47 percentage points) compared to the national average reduction (0.92 percentage points). In contrast, municipalities with land concentration above the mean do not exhibit a significant decline in cropland. However, both groups display a significant increase in bare ground, with a more pronounced and reliable effect in municipalities where land concentration is higher (columns 7 and 8). This suggests that small landowners respond to

[9]with the caveat that this estimanion is least significative.

extreme rainfall by reducing or even abandoning cropland, whereas large landowners may mitigate the impact by situating their crops in less environmentally vulnerable areas or reallocating cultivation within their landholdings.

With respect to land improvement practices, the results indicate that municipalities where farmers implement any form of land improvement exhibit a more pronounced reduction in cropland compared to the general trend. On average, 42% of the agricultural production units (UPAs) in a municipality do not utilize any soil improvement methods[10]. In municipalities where the proportion of non-investing UPAs exceeds the average, there is no significant reduction in cropland, but a notable increase in bare soil, which may indicate soil erosion. Conversely, in municipalities where farmers invest more in land improvement, there is no increase in bare ground, but a significant reduction in cultivated area (1.59 percentage points). This pattern suggests that municipalities with higher levels of land investment and engagement experience a more pronounced decline in cultivated areas, whereas in municipalities with lower investment, the primary effect is an increase in bare land area.

Regarding the heterogeneities associated with indigenous resguardos and National Nature Parks, Table 4 shows that municipalities below the mean in both categories exhibit results similar to the overall findings. This is expected, as 87% and 67% of municipalities fall below the mean for resguardos and PNN, respectively. For municipalities with above-average PNN areas, there is some indication of pasture reduction. However, the parallel trends assumption is not fully satisfied for pastures, limiting the robustness of this result.

[10]The census identifies various soil improvement methods including: organic fertilizers, chemical fertilizers, soil acidity correction, land burning, prayers, rituals, and ritualistic offerings. These practices reflect investment and a connection to the land.

Table 4: Municipal characteristic heterogeneities

	Credit application		Good land productivity		Poor land productivity		Land concentration		No land improvements		Indigenous' resguardos		National Nature Parks	
	Above mean (1)	Below mean (2)	Above mean (3)	Below mean (4)	Above mean (5)	Below mean (6)	Above mean (7)	Below mean (8)	Above mean (9)	Below mean (10)	Above mean (11)	Below mean (12)	Above mean (13)	Below mean (14)
Trees	0.21	-0.64	3.27**	-1.62	-0.60	0.56	-1.43	0.53	-1.37	0.64	-2.93	0.069	2.18	-1.07
	(1.21)	(1.20)	(1.48)	(1.05)	(1.39)	(1.07)	(1.45)	(1.06)	(1.37)	(1.09)	(3.23)	(0.89)	(1.79)	(0.96)
Pastures	-0.27	0.46	-0.38	0.27	0.65	-0.55	-0.23	0.24	0.76	-0.15	-0.16	0.054	-2.42*	1.03
	(1.07)	(0.68)	(1.17)	(0.67)	(1.00)	(0.75)	(0.81)	(0.84)	(0.94)	(0.79)	(1.73)	(0.64)	(1.41)	(0.64)
Crops	-2.06**	-0.09	-2.31**	-0.07	-1.46*	-0.46	-0.23	-1.47**	0.02	-1.59**	-0.61	-0.94**	-0.79	-0.98**
	(0.84)	(0.38)	(1.01)	(0.27)	(0.77)	(0.47)	(0.47)	(0.61)	(0.31)	(0.68)	(0.59)	(0.47)	(0.92)	(0.48)
Water	-0.08	0.38	-0.03	0.12	0.22	-0.03	0.44	-0.052	-0.06	0.29**	0.87	0.037	0.29	0.062
	(0.22)	(0.26)	(0.20)	(0.15)	(0.20)	(0.26)	(0.36)	(0.16)	(0.35)	(0.15)	(0.35)	(0.18)	(0.36)	(0.19)
Flood	-0.02	0.004	-0.01	0.10	0.04*	-0.05	0.32	-0.21	-0.17	0.10	-0.16	0.003	0.41	-0.15
	(0.23)	(0.21)	(0.07)	(0.092)	(0.023)	(0.28)	(0.32)	(0.15)	(0.35)	(0.092)	(0.057)	(0.17)	(0.25)	(0.19)
Built	0.29**	-0.009	0.18	0.08	-0.22	0.35***	0.12	0.191	0.16	0.08	-0.056	0.13	-0.50	0.34***
	(0.15)	(0.36)	(0.17)	(0.35)	(0.45)	(0.12)	(0.11)	(0.34)	(0.10)	(0.35)	(0.17)	(0.23)	(0.72)	(0.11)
Bare	0.27**	0.23*	-0.07	0.085	0.36**	0.15	0.37**	0.17*	0.43**	0.085	1.06	0.16**	0.09	0.30**
	(0.13)	(0.13)	(0.12)	(0.085)	(0.16)	(0.11)	(0.19)	(0.097)	(0.19)	(0.085)	(0.71)	(0.072)	(0.076)	(0.12)
Shrub	1.37*	-0.24	-0.82	0.33	1.16	-0.18	0.69	0.44	0.43	0.33	-0.32	0.64	0.51	0.48
& scrub	(0.75)	(0.96)	(0.99)	(0.69)	(0.84)	(0.92)	(1.02)	(0.80)	(0.19)	(0.69)	(1.42)	(0.68)	(0.92)	(0.80)
Mun.treated	101	155	102	154	119	149	99	157	102	154	23	233	68	188
Mun. always treated	2	10	1	11	7	5	8	4	5	7	3	9	3	9
N. municipalities	636	474	302	808	607	503	469	641	525	585	148	962	367	743
N. Obs	5088	3792	2416	6464	4856	4024	3752	5128	4200	4680	1184	7696	2936	5960

Notes: Each observation corresponds to the municipal-year level. Heterogeneities were estimated by running group regressions on subsets of the panel, divided based on whether observations were above or below the mean (see municipal summary statistics in Table 1). The table reports the number of treated municipalities and the total number of municipalities in each subset. Columns (1), (2), and (7)–(10) present heterogeneities based on aggregated municipal-level UPAs characteristics from the 2014 National Agricultural Census. Columns (3)–(6) display land productivity heterogeneities aggregated at municipal-level based on IGAC country land analysis. Columns (11) and (12) show heterogeneities based on the share of indigenous resguardos in the municipality. Finally, columns (13) and (14) report heterogeneities in the share of National Natural Parks at the municipal level.

6 Discussion

A growing body of literature demonstrates that climate shocks can influence land-use decision-making through multiple channels. On one hand, weather shocks may directly affect farmers' decisions regarding land us — such as expanding cropland, reallocating plantations, altering cropping systems, or diversifying agricultural outputs— due to their impacts on agricultural productivity, food security, and health. On the other hand, such shocks may prompt farmers to adopt strategies aimed at preserving their livelihoods and smoothing income, which may indirectly affect land use. These strategies include migrating, diversifying into non-agricultural activities, or engaging in practices that potentially compromise surrounding ecosystems (Girard et al., 2021). Also, depending on the severity of the shock the farmers responses could be different. For instance, should climate shock is not too severe, cope strantegies will prevail over other sustianable strategies (Desbureaux & Damania, 2018).

Nevertheless, the pontencial response from climate shock is highly dependent on the local components (Girard et al., 2021) such as socioeconomic, cultural and physical characteristics. In this paper I noticed that in general extreme rainfalls induce an reduction in cropland area and increament bare area. Still, when I exploit heterogeneities, the crop reduction effect is notably higher in cases where there seems to be more rural vulnerability to climate hazards. Another interesting result from heterogeneities is that in some of them there are signs of possible migration caused by the threaten event by the increasin on built-up areas.

Despite of the above, there is still the question of the effect persitence of the extreme rainfall effects on the land use decision taking. Figure A.3 presents the event studies from each type of land analyzed. It is observed that the effect for crops appears to be short term, only in the secon period there is a significant reduction for the periods following the shock. However, there is still no significant but consistent negative direction in the following coefficients. It is important to do future analysis where we can explore more treatment time with a new shocks with more information because I had the limitation of the period of 2015 to 2022 in which there where only two pikes of heavy precipitaion in colombia and jus a small group of municipalities had changed their behavior due to a climate shock for more than two periods. Regarding bare ground area Figure A.3g shows more consistent effects of climate shock on land abandonment for the next periods. Climate shock is observed to change the trend of behaivor of bare land area and these changes persist over time, at least for the first four periods.

Although analysis of the mechanisms is not the focus of this paper, evidence is presented here for some results of factors that could explain land use change in the territory. For example, there is much evidence in the literature that climate shocks induce changes in land yields that could also cause labor shifts in rural areas and increase the vulnerability of low productivity areas, creating incentives for farmers to change their behavior and develop adaptation strategies ranging from land use change, extracting resources from surrounding ecosystems to maintain their livelihoods or migrating in search of better opportunities. In this study, I notice land abandonements as a potantially concequence of migration due to climate risks. Although more empirical evidence is needed to demonstrate that these are the mechanisms and that they work properly.

7 Conclusion

This paper provides empirical evidence on the effects of extreme rainfall on land-use decisions in rural Colombia. Using high-resolution satellite data and a difference-in-differences framework with multiple time periods, I document that municipalities exposed to extreme rainfall events experience a significant reduction in cropland area, by an average of 0.92 percentage points, while bare land area increase, pointing out the abandonment of land.

Exploiting multiple dimensions of heterogeneity, I find that farmland reductions are significantly larger in municipalities characterized by higher credit application rates, small land ownership, and higher investments in land improvement. In particular, credit-constrained regions show signs of land abandonment, including an increase in bare land areas and built-up areas, potential indicators of rural out-migration. Land productivity further mediates these responses: municipalities with higher shares of unproductive land tend to experience both land abandonment and cropland reduction, while areas with better soils increase their built-up areas, potentially as a result of migration. These patterns underscore the differentiated capacities of rural communities to cope with climate shocks based on socioeconomic and agroecological characteristics.

Although this study does not aim to identify specific mechanisms, the findings are consistent with literature suggesting that climate shocks affect agricultural output, disrupt rural labor markets, and drive coping strategies such as migration or resource extraction. Preliminary evidence from the event study analysis shows that cropland responses may be short-lived, but effects on bare ground area appear more persistent, suggesting a lasting impact of rainfall shocks on land degradation and abandonment. However, the temporal scope of the data (2015–2022) limits the ability to assess long-term dynamics, as only two major rainfall peaks occurred during this window.

Ultimately, this paper highlights that land-use decisions are highly sensitive to extreme weather events and that vulnerability to climate shocks is spatially uneven. In particular, municipalities with poor-quality land or lower institutional and productive capacity are more likely to experience land abandonment and possibly long-term degradation. In contrast, areas with better endowments show signs of strategic adaptation through land reallocation. These results highlight the need for localized, resilience-focused policies that support smallholder adaptation and conservation of land productivity to avoid involuntary out-migration from rural areas and loss of food production capacity. Future work should explore the persistence of these effects and better isolate the mechanisms, such as changes in credit access, labor reallocation, or ecological degradations, that drive land-use transformation under climate stress.

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Appendix A Additional Figures and Tables

Figure A.3 present Callawat Sant'Anna event study for land use for each type of land analyzed in this paper: tree, pastures, crops, water, flood vegetation, buil-up area, bare ground and shrub & scrub. Especially in the case of pasture and water cover areas, the hypothesis of parallel trends is not fulfilled.

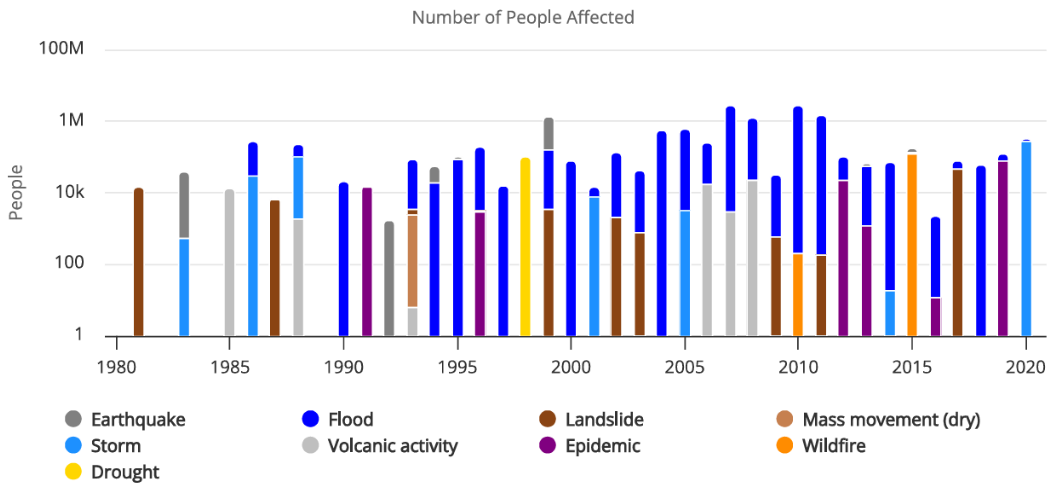
Table A.1: TWFE robustness over different treatment assignation.

Different deviation of the historic mean precipitation				
Dep. Variable:	1 Std. Dev. (1)	1.5 Std. Dev. (2)	2 Std. Dev. (3)	2.5 Std. Dev. (4)
Trees	-4.4	-0.56	-0.24	0.90
	(0.51)	(0.57)	(0.74)	(0.97)
Pastures	-0.05	0.25	0.17	-0.45
	(0.31)	(0.35)	(0.48)	(0.68)
Crops	-0.36*	-0.79***	-0.90**	-0.73
	(0.20)	(0.26)	(0.37)	(0.45)
Water	0.41**	0.65***	0.60***	0.45**
	(0.20)	(0.18)	(0.17)	(0.18)
Flood	-0.09	-0.08	-0.02	-0.06
& Vegetation	(0.6)	(0.07)	(0.09)	(0.09)
Built	0.09	0.17	0.11	0.02
	(0.07)	(0.10)	(0.16)	(0.27)
Bare	0.05	0.02	0.01	-0.004
	(0.04)	(0.04)	(0.05)	(0.056)
Shrub & Scrub	-0.24	-0.05	0.05	-0.37
	(0.37)	(0.44)	(0.53)	(0.67)
Municipalities treated	720	462	268	163
N. municipalities	1110	1110	1110	1110
N. Obs	8880	8880	8880	8880

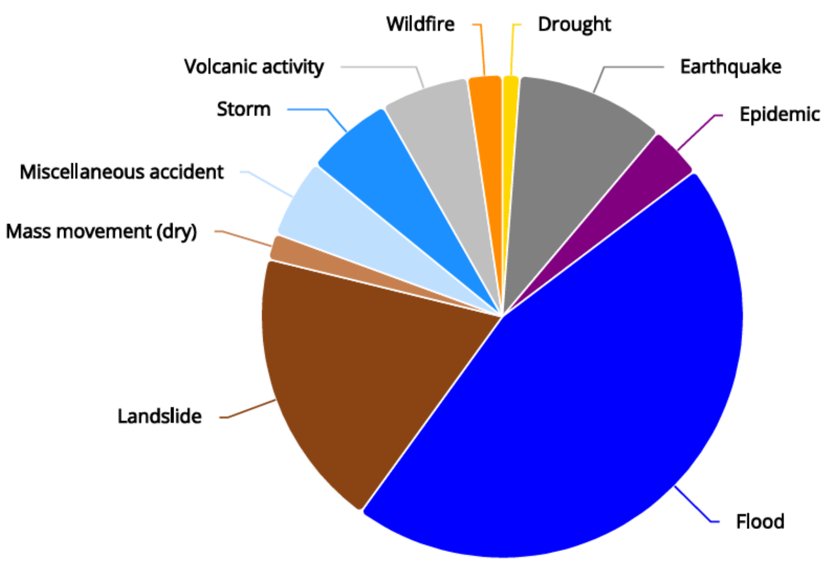
Notes: Each observation corresponds to the municipal-level data aggregated by year. Errors were clustered by municipality. $^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}p < 0.01$.

Figure A.1: Natural Hazard Statistics

(a) Key Natural Hazard Statistics for 1980-2020



(b) Frequency of Natural Hazards for 1980-2020



Notes: Figure A.1a presents the people affected by the principal natural hazard ocurrencies in Colombia for the years 1980 to 2020. Similarly, A.1b shows the portion of frequency that each natural hazard happened during the period of 1980-2020. The both figures has been taken from the World Bank's Climate Change Knowledge Portal (WB, 2021).

Table A.2: CS robustness over different treatment assignation.

	Different deviation of the historic mean precipitation			
Dep. Variable:	1 Std. Dev. (1)	1.5 Std. Dev. (2)	2 Std. Dev. (3)	2.5 Std. Dev. (4)
Trees	-0.76	-0.95	-2.1	0.54
	(0.58)	(0.65)	(8.6)	(1.1)
Pastures	-0.24	0.03	0.12	-1.9
	(0.39)	(0.46)	(0.61)	(0.77)
Crops	-0.21	-0.59**	-0.92**	-0.65
	(0.25)	(0.28)	(0.43)	(0.50)
Water	0.39***	0.34**	0.15	0.12
	(0.13)	(0.15)	(0.17)	(0.18)
Flood	-0.04	-0.06	-0.00	-0.02
	(0.08)	(0.09)	(0.16)	(0.16)
Built	0.08	0.19	0.12	0.04
	(0.09)	(0.13)	(0.21)	(0.34)
Bare	0.09	0.16**	0.24***	0.10
	(0.07)	(0.07)	(0.09)	(0.10)
Shrub	0.35	0.83	0.45	-0.21
& scrub	(0.47)	(0.51)	(0.64)	(0.77)
Municipalities treated	662	433	256	157
Municiplities always treated	58	29	12	6
N. municipalities	1110	1110	1110	1110
N. Obs	8880	8880	8880	8880

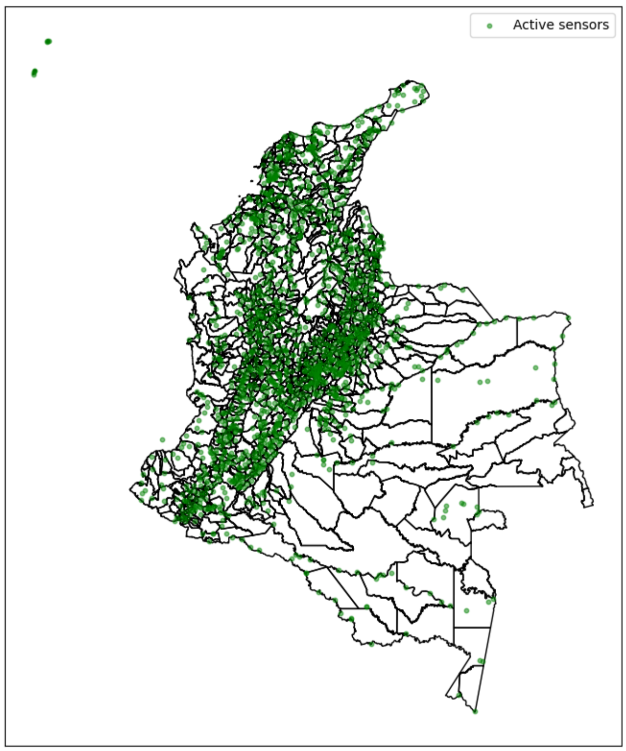
Notes: Errors were clustered by municipality. *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A.3: Disaggregated group-time average treatment effects by excluding municipalities with extreme dry episode.

Dep. Variable:	Trees	Pasture	Crops	Water	Flooded Vegetation	Built	Bare	Shrub & scrub	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
GAverage	0.15	-0.025	-0.90**	0.12	-0.010	0.13	0.22**	0.29	218
	(0.93)	(0.67)	(0.45)	(0.20)	(0.18)	(0.25)	(0.11)	(0.59)	
G2016	1.39	-1.73	0.45	0.27	-0.058	-1.29	0.32**	0.10	26
	(4.32)	(3.23)	(0.57)	(0.83)	(0.070)	(1.95)	(0.16)	(2.13)	
G2017	3.88	-1.02	-3.16	0.19	0.14	0.26	0.23*	0.94	40
	(2.81)	(1.58)	(1.98)	(0.50)	(0.27)	(0.23)	(0.12)	(1.90)	
G2018	-2.34	5.08***	-0.42	-0.034	0.26**	-0.086	0.27*	-2.82*	10
	(1.84)	(1.86)	(0.43)	(0.20)	(0.12)	(0.098)	(0.16)	(1.71)	
G2019	4.82	-2.27	0.28	-0.048	0.041	-0.25	0.047	-2.96***	5
	(3.83)	(2.67)	(2.60)	(0.68)	(0.037)	(0.76)	(0.081)	(0.87)	
G2020	-0.98	0.94	0.37	-0.17	-0.45	0.39	-0.32	0.20	13
	(1.80)	(2.50)	(0.61)	(0.22)	(0.46)	(0.27)	(0.36)	(2.29)	
G2021	-1.03	0.32	-1.58**	0.21	0.50*	0.36**	0.0081	1.04	55
	(1.28)	(0.97)	(0.66)	(0.24)	(0.30)	(0.16)	(0.19)	(0.94)	
G2022	-1.31	0.15	0.048	0.040	-0.45	0.41**	0.45	0.096	69
	(1.37)	(1.06)	(0.53)	(0.38)	(0.45)	(0.17)	(0.28)	(0.87)	

Notes: This aggregation provides the average effect of participation in the treatment for observations in each group averaged across all time periods after that group becomes treated (Callaway et al., 2024). The length of exposure to treatment affects the average effect, and they are groups with different level of exposure. N represents the municipalities treated. This table differs from table 3 on the number of observation because here I exclude municipalities that have been ever experienced extreme dry episode in the period analyzed. Cluster errors by municipality. *$p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

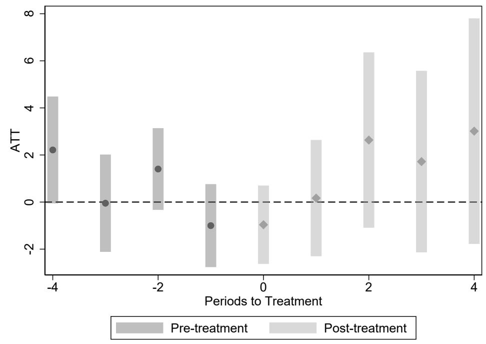
Figure A.2: IDEAM sensors location



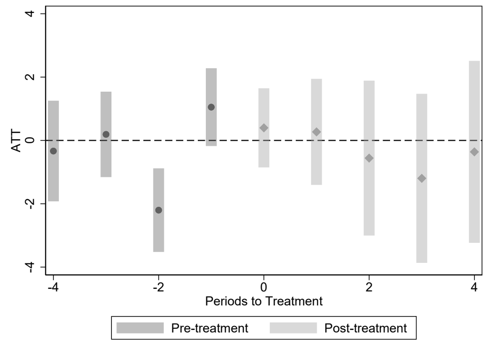
Notes: This figure displays the locations of active IDEAM sensors utilized in this study, distributed across 1,110 different municipalities in the country. There is a noticeable concentration of sensors in the central zone of the country, extending from the southwest to the north. This distribution aligns with the three major mountain ranges, which significantly influence the country's climate and precipitation patterns. However is evident lack of sensor in some peripheral areas in the Orinoquia and Amazonia.

Figure A.3: Event studies by each type of land using CS estimation

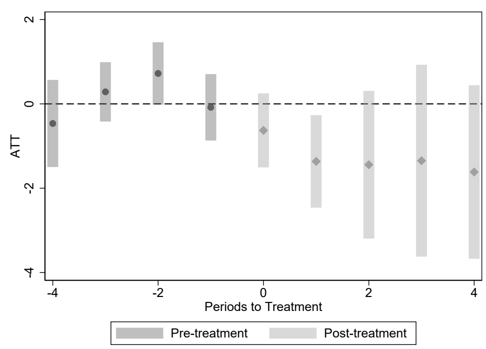
(a) Trees



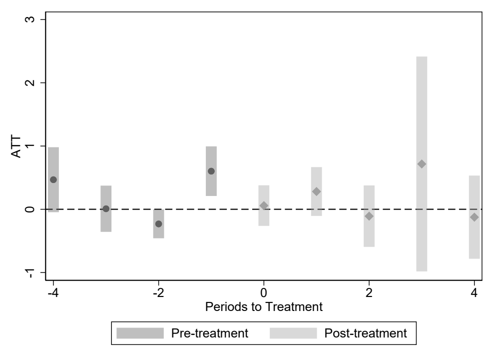
(b) Grass



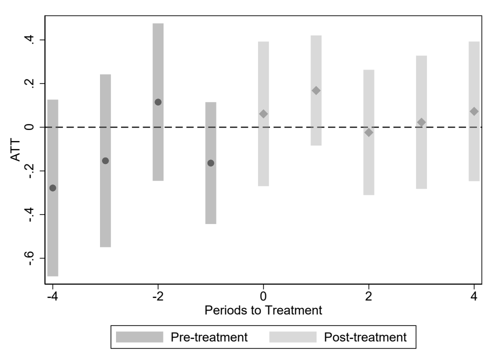
(c) Crops



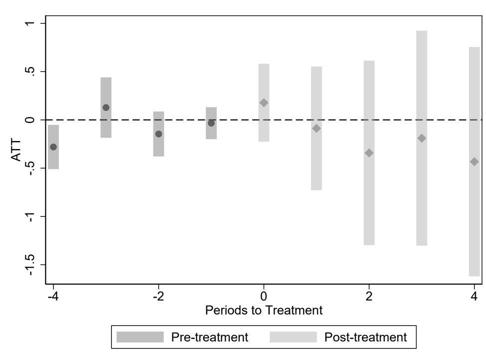
(d) Water



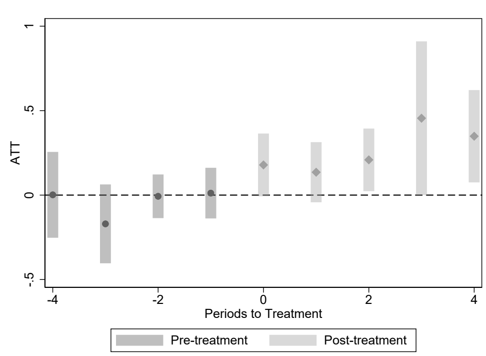
(e) Flooded Vegetation



(f) Built-up area



(g) Bare ground



(h) Shrub & scrub

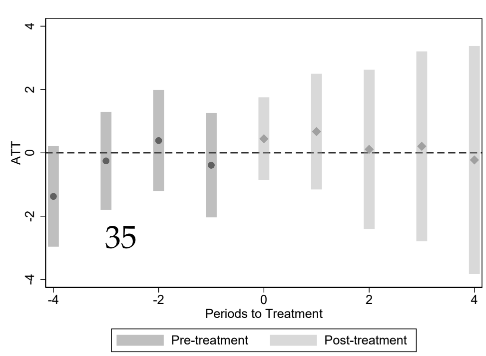
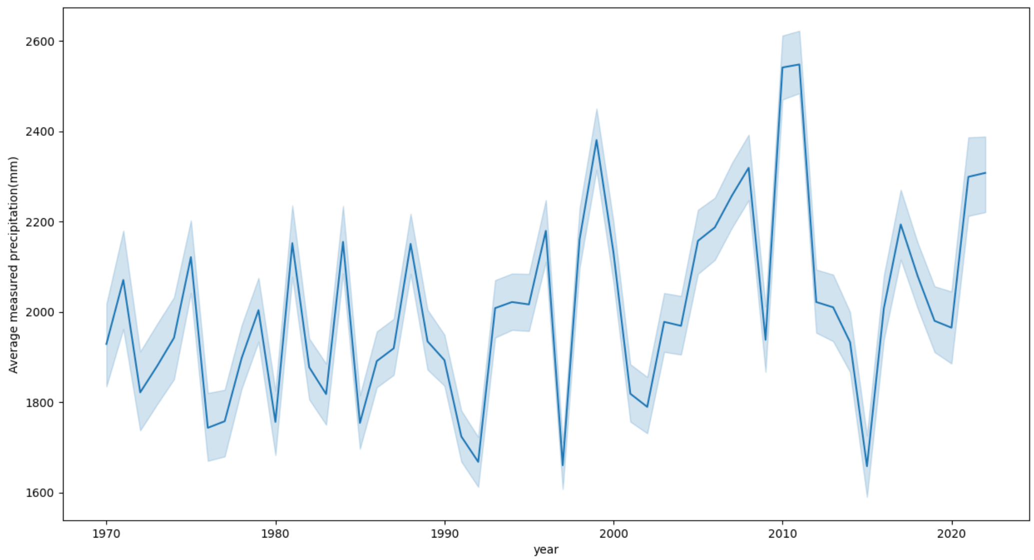


Figure A.4: Precipitation time serie



Notes: This figure displays the annualized average precipitation in milimeters (mm) at all active sensors in Colombia.