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Impact of Drought and Floods on Agricultural Household Poverty in Burkina Faso

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Abstract

The aim of this article is to analyze the impact of extreme weather events specifically droughts and floods on the monetary and food poverty of agricultural households in Burkina Faso. To do so, we use data from the Permanent Agricultural Survey (EPA) along with climate data provided by the Burkina Faso National Meteorological Directorate. The climate variables representing drought and flood are constructed using the Standardized Precipitation Evapotranspiration Index (SPEI), a recognized indicator for capturing hydrometeorological anomalies.

Since the dependent variable (poverty) is binary, we apply a logit model to estimate the likelihood of poverty occurrence based on climate shocks and the socioeconomic characteristics of households.

The empirical results show that both types of extreme events significantly increase the risk of poverty among agricultural households, with drought having a more pronounced effect. Specifically, experiencing a drought increases the likelihood of poverty by more than three times, compared to a 1.5-fold increase in the case of floods. This highlights the severe vulnerability of farming households to prolonged water deficits, which directly affect agricultural yields and food security.

Furthermore, the analysis reveals that certain household characteristics exacerbate vulnerability to poverty. Households with more than 14 members face a significantly higher probability of falling into both monetary and food poverty. In contrast, income diversification reduces poverty risk, as it strengthens the economic resilience of farming households in the face of climate shocks.

Finally, our results underscore a key gender dimension: households headed by women are less likely to experience monetary poverty compared to those headed by men. This may be due to differences in financial management strategies or a more cautious approach to income diversification.

In sum, this study highlights the urgent need for public policies that integrate both climatic and social dimensions to effectively combat rural poverty in the context of increasing climate variability.

Keywords: Burkina Faso; floods; droughts, SPEI, poverty, logistic modelling.
JEL Classification : Q18; Q54 ; O12 ; O13
Type du papier : Recherche empirique

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1. Introduction

In Burkina Faso, approximately three-quarters of the population live in rural areas (INSD, 2020). In these regions, agriculture constitutes not only the primary source of income for households but also serves as a cornerstone of the country's macroeconomic development, contributing significantly to GDP, employment, and food security. Despite considerable potential for agricultural growth thanks to abundant arable land and a young labor force the sector remains largely underdeveloped. Agricultural activities are predominantly small-scale and traditional, with minimal use of improved inputs or technologies. Most farms are heavily dependent on rainfall due to the lack of adequate irrigation infrastructure, making agricultural productivity highly susceptible to climatic conditions.

This structural dependence on rainfall exposes rural livelihoods to severe climate risks. In fact, climate change represents a growing and pervasive threat across sub-Saharan Africa, particularly for rural populations whose subsistence is closely tied to environmental stability. Rain-fed agriculture, which accounts for most of the cultivated land in the region, is extremely sensitive to climate shocks such as erratic rainfall, prolonged droughts, and increasingly frequent floods (FAO, 2018). According to the Centre for Research on the Epidemiology of Disasters (CRED, 2024), Africa recorded 60 extreme weather events in 2023 alone including droughts, floods, wildfires, and heatwaves that collectively affected around 12.5 million people and generated an estimated $13.7 billion in economic damages. These climate-related events are not just natural disasters; they act as barriers to sustainable development by exacerbating existing vulnerabilities and undermining progress toward key international commitments, including Sustainable Development Goal 1 (SDG 1), which aims to end poverty in all its forms (IPCC, 2022; Jafino et al., 2020).

Burkina Faso is particularly vulnerable to climate change due to its Sahelian climate, characterized by low and irregular rainfall. Projections by the National Meteorological Agency indicate a significant rise in average temperatures by 0.8°C by 2025 and 1.7°C by 2050 which could dramatically intensify evapotranspiration and further stress already fragile ecosystems and farming systems (SP/CONEDD, 2007). The country receives about 206.9 billion cubic meters of rainfall annually, yet only 16% of this water infiltrates the soil, while nearly 80% evaporates underscoring the inefficiencies in water retention and the urgent need for climate-resilient agricultural practices.

In this context, understanding the socioeconomic impact of climate extremes particularly droughts and floods on rural agricultural households becomes essential. Although poverty has been extensively analyzed in Burkina Faso, existing research overwhelmingly indicates that rural areas remain the epicenter of poverty. Nearly 90% of the poor reside in rural regions, a pattern strongly linked to the predominance of low-yield, subsistence-based agriculture that struggles to withstand environmental shocks (Lachaud, 2000; Nouve et al., 2010; Ouarme et al., 2010; Ouedraogo, 2009; Wetta & Yerbanga, 2007).

Beyond climatic factors, other studies emphasize the structural barriers that perpetuate rural poverty, including inefficiencies in agricultural production (Noufé, 2020), inadequate access to credit and financial services (Sanfo, 2010), weak infrastructure, and limited educational attainment. While these factors are undeniably important, the role of climate variability as a driver of poverty has been less rigorously examined particularly using real meteorological data. The seminal work by Reardon and Taylor (1996), which considered agro-climatic zones in analyzing poverty, laid early groundwork in this area but did not incorporate quantitative climate indicators such as temperature trends or rainfall anomalies.

Yet, in a country where agriculture is overwhelmingly rain-fed, the omission of actual climate variables in poverty analysis represents a significant gap. Climatic conditions have a direct influence on crop yields, labor productivity, market access, household income, and ultimately

food and economic security. For example, a delayed rainy season can shorten the growing cycle, reduce output, and increase the risk of food insecurity and income loss among already vulnerable households.

This study seeks to address this research gap by integrating real-time meteorological data into the analysis of poverty determinants at the household level. Specifically, we combine data from the 2020 Permanent Agricultural Survey conducted by the Ministry of Agriculture with localized climate indicators from the National Meteorological Directorate. Our empirical approach relies on logistic regression models that estimate the likelihood of a household falling into monetary or food poverty as a function of exposure to climate shocks, controlling for a variety of socioeconomic and demographic variables.

The article is structured as follows: Section 2 presents the theoretical framework on the link between climate change and poverty; Section 3 is devoted to the empirical literature review on the relationship between climate change and poverty; Section 4 defines the main variables related to poverty and climate (drought and flooding); Section 5 outlines the chosen methodological approach; Section 6 analyzes the empirical results; and finally, Section 7 offers conclusions and recommendations.

2. Theoretical Framework: The Link Between Climate Change and Poverty

The relationship between climate change and poverty has garnered increasing attention in the scientific literature due to its profound implications for food security, livelihoods, and economic stability, particularly in developing countries (IPCC, 2022; Schleicher et al., 2018). Several theoretical approaches help explain how the effects of climate change can exacerbate poverty, especially in rural areas.

- ***The Vulnerability Theory***

The vulnerability approach (Chambers, 1989; Adger, 2006) posits that poverty is not solely the result of low income but also of increased exposure to risks and limited capacity to cope with them. Poor households, which heavily depend on natural resources such as land, water, and forests (Miller et al., 2022), are the most exposed to the adverse effects of climate change. In particular, those practicing rain-fed agriculture often lack the resources needed for adaptation (savings, credit, insurance, information), which heightens their vulnerability.

- ***The Poverty Climate Change Vicious Cycle***

According to Hallegatte et al. (2016), the relationship between poverty and climate change is circular and cumulative. On one hand, poor populations are more vulnerable to climate shocks; on the other hand, these shocks worsen their poverty by destroying their assets (crops, livestock, shelters) and reducing household income. This dynamic can lead to chronic poverty or even intergenerational poverty transmission (Dercon, 2005).

- ***The Climate Shocks Approach***

The work of Carter et al. (2007) and Elbers et al. (2007) highlights the impact of climate shocks (droughts, floods, cyclones) on the ability of rural households to sustain agricultural investments. Faced with a heightened risk of crop failure, these households tend to reduce their productive spending and adopt short-term coping strategies (such as selling livestock or reducing consumption), thereby compromising their food security and prospects for escaping poverty.

- ***Structural Inequalities and Climate Justice***

According to climate justice theory (Schlosberg, 2007; Sen, 1999), the poorest populations are

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both the least responsible for climate change and the most affected by its impacts. This structural inequality raises important questions about the fairness of adaptation resource allocation. In sub-Saharan Africa, rural areas already facing economic hardship are the most exposed to extreme climatic conditions, which further marginalize them (Béné, 2009; Wunder et al., 2018).

- ***Amplified Multidimensional Poverty***

Poverty, particularly in rural settings, is multidimensional and affects various aspects of well-being: income, nutrition, health, education, and housing (Alkire & Foster, 2011). Climate change simultaneously impacts these dimensions by reducing access to food (due to drought), increasing waterborne diseases (due to floods), and limiting school attendance (due to labor demands on children), among others. Projected agricultural yield losses of 5% to 30% by 2080 (Biewald et al., 2015), even with adaptation measures, are likely to intensify these inequalities.
Hypotheses Derived from the Theoretical Framework

- *H1: Climate change has an aggravating effect on both monetary and food poverty.*
- *H2: Extreme climate events (droughts and floods) are key transmission channels through which climate change affects rural poverty levels.*

3. Literature review on the link between extreme weather event and poverty

The link between climate change and poverty has received increasing attention in the scientific literature, particularly because it is the poorest populations who suffer the most severe consequences (Schleicher et al., 2018). These populations rely heavily on natural resources such as agricultural land, water, and forests for their livelihoods (Miller et al., 2022). A study conducted in South Africa by Azzarri & Signorelli (2020) reveals that smallholder farmers are significantly more exposed to climate hazards (droughts and floods) than large-scale producers or non-agricultural households, due to their limited adaptive capacity.
In this context, it becomes imperative for societies to strengthen their resilience to climate-related disruptions, especially in rural areas. Hallegatte et al. (2018) emphasize that the relationship between rural poverty and vulnerability to climate shocks is bidirectional: on one hand, poverty makes populations more vulnerable to climate shocks; on the other, these shocks deepen poverty by reducing households' productive assets and incomes.
Indeed, a major climate shock can worsen the precarity of already poor households, push them further into poverty, or trap them in a vicious cycle of poverty and inadequate coping strategies (Asare-Nuamah et al., 2021; Tongruksawattana & Wainaina, 2019). Numerous studies have shown that climate change significantly increases the risk of impoverishment, particularly in rural areas heavily dependent on agriculture (Hallegatte et al., 2016). In Burkina Faso, Noufé (2020) demonstrated that climate shocks reduce agricultural yields, thereby lowering rural household incomes. Watinan et al. (2024) further highlight that the effectiveness of public policies particularly in tackling inflation, promoting the agricultural sector, and managing climate risks plays a critical role in poverty reduction.

H1: Climate change has an aggravating effect on both monetary and food poverty.

The 2015–2016 El Niño episode clearly illustrates the severity of some climatic events. It was one of the most powerful tropical phenomena of the 21st century, triggering a prolonged drought in West Africa, reduced atmospheric humidity, increased evapotranspiration, and exceptionally high temperatures (Rifai et al., 2019). The consequences were severe for small cocoa producers, whose incomes dropped due to the decline in global supply (Abdulai et al.,

2018; ICCO, 2016). Drought is now recognized as the leading abiotic threat to agriculture in West Africa (Gateau-Rey et al., 2018; Seutra Kaba et al., 2021).

In India, Krishna (2006) showed that a household affected by a drought was 15 times more likely to fall into poverty. More broadly, droughts as extreme climate shocks increase the uncertainty of agricultural investments, leading farmers to reduce production expenditures, thereby limiting their ability to improve their living conditions (Elbers et al., 2007). Similar findings have been observed in countries such as Ethiopia, Honduras (Carter et al., 2007), and the Democratic Republic of the Congo (Béné, 2009). Moreover, research suggests that households living in particularly hot and arid zones are more vulnerable to poverty due to low agricultural yields (Wunder et al., 2018). In such contexts, forests play a vital role by providing alternative income sources, helping to mitigate the negative effects of climate on household livelihoods.

Recent modeling estimates that by 2030, climate change could cause agricultural yield losses of around 5%, and up to 30% by 2080 even when adaptation measures are taken into account (Biewald et al., 2015). These losses are likely to exacerbate rural poverty by reducing agricultural income and limiting access to food. Additionally, lower production can drive up food prices, further increasing the vulnerability of the poorest households to food insecurity.

However, according to Jacoby et al. (2014), the impact of rising food prices on farming households is not uniform: under certain conditions, farmers may benefit from higher prices. Other researchers, however, argue that when production losses are substantial, they largely offset these potential gains and deepen poverty (Hertel et al., 2010). A study by Ahmed et al. (2009), conducted in Malawi, Mexico, and Zambia, found that climate-induced food price hikes led to a 20–30% increase in poverty among non-agricultural households.

H2: Climate change affects poverty through both droughts and floods.

4. Research Methodology

We use the logistic modelling to estimate the impact of climate variability on agricultural household poverty. This choice is justified by the fact that the dependent variable is binary, taking 1 if the household is poor and 0 otherwise. The ordered logit model is specified as follows:

$$Y_i^* = \beta X_i + \varepsilon_i$$

Where $Y_i^*$is a latent variable (the dependent variable) defined as follows: it defines the probability for a household ii to be poor or not. X_i represents the vector of explanatory variables; β is a vector of parameters associated with the explanatory variables, and ε_i is an error term.

For the analysis of these binary variables, the intuition is that the realization of Y_i follows a decision rule controlled by X_i such that:

$$Y_i = \begin{cases} 1\ poor \\ 0\ \ non-poor \end{cases}$$

In this form, the model is not a deterministic model but a probabilistic model. By designating ε_i as the error term; $\frac{\varepsilon_i}{\sigma_\varepsilon}$ follows a logistic distribution function $F_{ij}(X, \beta)$.

$F_{ij}(X, \beta)$ corresponds to the probability associated with the occurrence of event j. In our case, it corresponds to the probability that a household is poor. This poverty is given by: $Prob = (Y_i = j)$, In our case, it corresponds to the probability that a household is poor. This probability is given by X and the parameter vector β.

The vector X includes variables related to the household head's characteristics.

The estimated empirical model is as follows:

$$Y_i = \alpha + \ \alpha_1 Drought_i + \alpha_2 Flood_i + \beta X_i' + \varepsilon_i$$

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Where i is the index of the agricultural household, Y_i is the poverty status of agricultural household i, $X_i'$is a vector of other explanatory variables. These explanatory variables include the socioeconomic characteristics of the household.

4.1. Variables

- ***Monetary poverty***

In the framework of our study, we use two poverty indicators: a monetary indicator and a non-monetary indicator. According to our monetary indicator, a household is considered poor if the total income per adult in the household is below the absolute monetary poverty threshold, which is 194,629 CFA francs at current prices in Ouagadougou (INSD, 2018).

- ***Non-monetary poverty***

Food poverty is a significant concern for farmers in rural areas. In addition to the monetary poverty indicator, we incorporate into our analysis a non-monetary poverty indicator based on food consumption scores. Food consumption scores (FCS) measure both the quality and quantity of the diet and primarily capture dimensions of availability and access (Dabalen & Paul, 2014).
In the context of this study, the food consumption score measures food poverty. The household's FCS is calculated by multiplying the total consumption frequency over the past 7 days by weighting each food group and then summing the results for all food groups consumed by a given household. This indicator distinguishes the approach to poverty by basic needs.
The maximum score is 112, meaning that if a household consumes all food groups every 7 days, it will have a consumption score equal to 112. The score is compared to a predefined threshold, so it is considered poor when it is below 21, considered borderline when it is between 21 and 35, and deemed acceptable when it is above 35.

Table 1: Monetary and food poverty

Poverty	**Modalities**	**Proportions (%)**
Food poverty	1 : Poor 0 : Non-poor	12,78 87,22
Monetary poverty	1 : Poor 0 : Non-poor	41,55 58,45

Source: Author

- ***Analysis of the discrepancy/concordance between the two poverty thresholds***

Our analysis of Table 2 shows that depending on the chosen threshold, we do not measure the same poverty phenomenon. Indeed, a household can be poor according to the monetary poverty threshold and not be so according to the food poverty threshold. We observe a 54% discordance between the two poverty measures. In other words, only 46% of agricultural households are poor according to both the monetary poverty threshold and the food poverty threshold. It would therefore be interesting to study the effect of climatic conditions on these two variables separately.

Table 2: Cross-table between monetary poverty and food poverty

Food poverty	Monetary poverty	
	Non-poor	Poor
Non-poor	18,32	41,55
Poor	12,78	27,35
Total	31,1	68,9

Source: Author

- ***The Standardized Precipitation Evapotranspiration Index (SPEI)***

Several indices allow for the detection of drought and measurement of climatic conditions. Among these indices, we can mention the Palmer Drought Severity Index (PDSI) (Palmer & Denny, 1965). This index measures soil moisture and drought based on previous precipitation, moisture input, runoff, and surface evaporation. It is based on soil-water balance. The PDSI captures the essential characteristics of climatic conditions but faces issues such as calibration, spatial comparison, and subjectivity when comparing results to drought conditions. The Standardized Precipitation Index (SPI) uses precipitation to measure drought over time.

This index is easier to calculate and allows for comparisons over time and space, but it is based solely on precipitation and does not account for variables such as temperatures or water retention capacity (Vicente-Serrano et al., 2010). The Standardized Precipitation Evapotranspiration Index (SPEI) is used in this work. It combines both methods by incorporating the sensitivity of the PDSI to changes in temperature and evapotranspiration and the simplicity of the SPI. This index is based on the difference between monthly or weekly precipitation amounts P_{it} and evapotranspiration PET_{it}, known as the water balance.

$$D_{it} = P_{it} - PET_{it}$$

Where *i* represents the location of the observation and *t* the period. The data used are sourced from the National Meteorological Agency of Burkina Faso. The raw data on precipitation and evapotranspiration from the country's ten meteorological stations are monthly and date back to 1986. Precipitation is measured in millimeters, and evaporation calculations (a package available in R) are based on the Penman-Monteith equation, which utilizes mass transfer and energy balance with temperature and vegetation conductance. The use of a log-logistic distribution enables the calculation of the SPEI from the water balance data (Liu & Liu, 2019). We choose a six-month period, from May to October, to focus on the rainy season, which is crucial for agricultural households (Stagge et al., 2014).

After calculating the SPEI at each station and considering the lack of information on household geolocation, we assigned the scores of the considered months to each region. In other words, if there is no meteorological station in the region, we assign the calculated index based on observations from the nearest station. Furthermore, if a household lives closer to the meteorological station of the neighboring region than to its own region's station, we assign it the index of the nearest station.

Drought-humidity categorization: extremely humid: above 2.00; severely humid: 1.5 to 1.99; moderately humid: 1.00 to 1.49; near normal: -0.99 to 0.99; moderate drought: -1.49 to -1.00; severe drought: -1.99 to -1.50; extreme drought: less than -2.00. For our study, we create a flood variable, which is a dichotomous variable, taking 1 if the household has a SPEI greater than 1.5 and 0 otherwise. To account for the effect of drought, we also create a drought variable, which takes 1 if the household has a SPEI less than -1.5 and 0 otherwise.

Table 3: SPEI (drought and floods)

Levels of measurement						
> 2	**1.5-1.99**	**1.00-1.49**	**-0.99-0.99**	**-149-1.00**	**-199-1.5**	**< -2**
Extremely humid	Severely humid	Moderately humid	Near normal	Moderate drought	Severe drought	Extreme drought

Source : Author

- ***Socioeconomic characteristics of the household***

Gender of the household head: Gender differences are a determining factor in the poverty of agricultural households. With this variable, we aim to verify if the risk of poverty is higher for households led by women compared to when the household is led by a man. Note that due to their gender, women are naturally more vulnerable than men in rural areas. This is primarily due to cultural norms that dictate that women should solely take care of their husbands and children, as well as their lower level of education, which is generally lower than that of men

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because in these environments, they are married at a very young age or spend all their time on household chores.

Education level of the household head: This includes formal education, literacy, rural school, and medersa (Arabic studies). The education level is measured by the household head's schooling level. Considering this variable will allow us to understand the role of extension services because education is essential for accessing extension services. Having a certain level of education also enables household heads to have additional income. The education level was grouped into two categories: the first category, termed "non-literate," consists of households with no educational level. The second category, termed "literate or at least primary level," includes households where the household head has a minimum level of literacy (rural school or medersa) or at least primary level in formal education. The majority of household heads have no educational level (74%), only 26% have at least a primary level.

Marital status of the household head: We considered two types of marital status for household heads. They are either single or in a couple. Household heads in a couple represent 84% of households (see Table 4). It is worth noting that household members constitute the workforce for households. Being in a couple thus increases the labor force for agricultural plots.

Household size: The total number of members residing in the household (children and adults) provides an idea of the household's human capital as well as its food expenses. It all depends on the household composition; if the number of active members exceeds that of inactive members (the elderly and children), this constitutes an advantage for the household because household members constitute the main workforce for working on agricultural plots. The average household size is 10 with a standard deviation of 7. We divided household size into three groups[1] ([1-7[, [7-14[, and more than 14 people), using the first category [1-7[as the reference category in the model specification. The majority of agricultural households consist of more than 7 people (60%) (see Table 4). According to the literature, an increase in household size is expected to lead to an increased risk of poverty.

Household income source diversity: This refers to the total number of income sources of the agricultural household head. This variable is important as it provides an idea of the household's resilience to income shocks. If the household has multiple income sources and one of the sources is affected by an exogenous shock, the resulting losses could be offset by income from other activities. An increase in income source diversity is expected to have a negative impact on food poverty. Three types of income diversity are considered: low diversity (a single income source), medium diversity (two income sources), and high diversity (more than two income sources). Table 4 shows that agricultural households have a high diversity of income sources (50%). In addition to agriculture, agricultural households engage in livestock farming (84%), craftsmanship (65%), as well as small-scale trading.

Table 4 : Statistics of qualitative variables

[1] *The fertility rate in Burkina Faso in 2016 was 5 children per woman (AfDB, 2016). Based on this fertility rate, we defined the first class [1-7[. For the intermediate class, we added one standard deviation to the upper bound of the first class (this class contains the average household size). In order to have relatively balanced classes, the third class includes all households larger than 14.*

Variables	***Modalities***	***Fréquence (%)***
Floods	Yes	15
	No	85
Drought	Yes	61
	No	39
Diversity of income sources	Law	23,24
	Mean	27,54
	High	49,23
Household size	1 : [1-7[	35,46
	2 : [7-14[	41,70
	3 : above to 14	22,84
Gender of the household head	Man	67,4
	Woman	22,6
Literacy	Yes	25,85
	No	74,15
Marital status	1 : single	15,99
	2 : couple	84,01

Source: Author

4.2. Data survey

We use data from the Agricultural Survey (EPA) conducted in 2020. The Permanent Agricultural Survey is carried out by the Ministry responsible for agriculture among agricultural households. The objective of this survey is to support household resilience towards a sustainable resolution of food insecurity situations. These results will help assess household-level food security indicators to better understand their food situation to contribute to the harmonized framework for analyzing food and nutritional vulnerability. It covers all 13 regions of Burkina Faso.

This is a two-stage survey. The first stage, also referred to as the sampling unit, is the commune as defined by the General Population and Housing Census (RGPH) in 1996. Communes are sampled with a probability proportional to their size in agricultural households.

The sampled agricultural household constitutes the secondary unit. The first-stage sample was drawn from 349 communes. A second-stage sample of 5037 households was drawn. Sampling was conducted in each commune with equal probability and without replacement, with 8 households selected for communes with small producers (stratum 1) and 5 households for communes with large producers (stratum 2)

5. Results et discussion

The effects of climate change on the risk of poverty are presented in Table 6. The relevance of the logistic modelling is evaluated by the likelihood ratio (Greene, 2003). Likewise, the likelihood ratio and Pearson's test show that the logit model is globally significant.

We use the Variance Inflation Factor (VIF) to assess the severity of multicollinearity (table 5). To obtain a more intuitive interpretation of the estimated coefficients, we consider the effect of a given variable on the odds ratio that an agricultural household will experience monetary or food poverty.

Table 5 : Collinearity Diagnostics

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Variables	VIF
Drought	1.01
Floods	1.02
Household size	1.01
Diversity of income sources	1.01
Gender of the household head	1.03
Marital status	1.04
Literacy	1.02
Mean	1.02

Source : Author

Table 6 : Agricultural Loss Factors

Variable	**Modalities**	**Proportions**
Agricultural Loss Factors	1: no loss	65,42
	2: Floods	6,17
	3: Drought	25,01
	4: anothers factors	3,40

Source : Author

Table 7 presents the results of the logistic regression, where the dependent variable is the risk of an agricultural household falling into poverty—whether monetary or food-related. The interpretation of the results relies on the analysis of the odds ratio. An odds ratio greater than 1 indicates a positive relationship: in other words, households belonging to that category are more likely to experience poverty compared to the reference category. Conversely, an odds ratio less than 1 suggests a lower likelihood of poverty for that group.

The results show that climate change, through droughts and floods, has a significant and negative effect on both monetary and food poverty levels among agricultural households. Specifically, living in a commune affected by drought increases the risk of monetary poverty by a factor of 3.82 and the risk of food poverty by a factor of 1.5 (coefficients significant at the 1% level). In comparison, floods also raise the risk, though more moderately, with an odds ratio of 1.33 for monetary poverty and 1.17 for food poverty (also significant at the 1% level).

According to data from the Permanent Agricultural Survey (PAS, 2020), drought accounts for about 30% of agricultural losses, compared to just 6% for floods. These production losses increase the likelihood of households falling into poverty, especially food poverty. Furthermore, drought alters household behavior: fearing future losses, farmers tend to reduce their investments. While this response may seem rational, it can trap them in poverty. Drought also leads to reduced agricultural income, worsening their economic vulnerability.

These findings are consistent with those of Krishna (2006), who found that a household previously affected by drought was 15 times more likely to fall into poverty. Other studies (Elbers et al., 2007; Carter et al., 2007; Béné, 2009) confirm this negative relationship between climate shocks particularly drought and poverty risk in countries such as Ethiopia, Honduras, and the Democratic Republic of the Congo. Similarly, Wunder et al. (2018) highlight that rural households in hot and dry regions are more exposed to poverty due to lower agricultural incomes. Falkenmark et al. (2019) argue that water scarcity exacerbates socio-economic inequalities, especially in arid and semi-arid regions, where poor households are the least equipped with irrigation technologies.

The analysis also reveals that literacy significantly reduces the risk of poverty. Households headed by individuals with at least primary education have an odds ratio of 0.9 for monetary poverty and 0.08 for food poverty (the latter significant at the 10% level), compared to households headed by illiterate individuals. Literacy improves agricultural productivity, facilitates access to non-agricultural income-generating activities, and supports better adoption of climate resilience strategies, particularly through agricultural extension services. These

services expose households to new farming techniques, thereby boosting yields and reducing the risk of poverty.

These results support the findings of Noufé (2020), who showed that the education level of the household head reduces the risk of monetary poverty among Burkinabè farming households. Similarly, Fafchamps and Quisumbing (1999), in their study on rural households in Pakistan, observed a positive correlation between the education level of the household head and rural income. Attanasso (2004) concluded that agricultural households headed by uneducated women face a particularly high risk of poverty.

Moreover, income source diversification is a key lever for reducing poverty risk. Households with moderate (two sources) or high (three or more sources) income diversification have odds ratios of 0.3 and 0.12 respectively, compared to those with only one source of income. Diversifying income through activities such as handicrafts or small-scale trade is therefore an effective strategy for reducing economic vulnerability, especially in the face of climate shocks.

Lastly, household size is an aggravating factor for poverty. Households with more than seven members have an odds ratio of 1.29 for monetary poverty, which is statistically significant at the 1% level. This can be explained by the higher number of dependents (children, elderly) to support. The high dependency ratio estimated at 80% in Burkina Faso (INSD, 2020) reinforces this vulnerability. Furthermore, households headed by women face a higher risk of food poverty than those headed by men, highlighting structural gender-based inequalities.

Table 7: Effects of Extreme Climate Events on Poverty

	Monetary poverty	Food poverty
Variables	(1)	(2)
	Odds ratios	Odds ratios
Drought (ref : no)	**3,828*** **	**1,585****
	(0,863)	(0,161)
Floods (ref : no)	**1,330***	**1,717****
	(0,353)	(0,449)
Household size (ref : [1-7[**)**		
[7-14[	1,29***	1,02***
	(0,54)	(0,126)
More than 14	1,81***	1,25***
	(0,87)	(0,76)
Diversity of income sources (ref: Low)		
Mean	0,363***	0,868
	(0,173)	(0,101)
High	0,12*	0,16
	(0,34)	(0,246)
Gender of the household head (ref: man)	0,590***	0,918
	(0,120)	(0,143)
Literacy (ref : no)	0,909*	**0,088***
	(0,078)	(0,085)
Marital status (ref : single)	0,91	0,85
	(0,56)	(0,98)
Mean VIF=1,03		
LR chi2(22)	589,56	
Observations	4956	4956
Pseudo R^2	0,10	0,11

*Note: *, **, *** respectively indicate the significance of the coefficients at 10%, 5% et 1%.*

Source: Author

6. Conclusion

The aim of this article was to analyze the effects of climate change through extreme weather events such as droughts and floods on monetary and food poverty among agricultural households. To assess these climate events, we used the Standardized Precipitation

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Evapotranspiration Index (SPEI), a composite indicator that incorporates both precipitation and evapotranspiration, thus allowing for a more accurate evaluation of water deficits or surpluses. Monetary poverty is approximated by the household head's income level, while food poverty is measured using the Food Consumption Score, a widely used indicator to assess the diversity and nutritional quality of diets.

The study is based on data from the 2020 Permanent Agricultural Survey. We adopted both a monetary poverty threshold (based on income) and a non-monetary poverty threshold (based on food consumption). The results reveal that both forms of climate extremes droughts and floods significantly increase the risk of poverty among agricultural households. These findings are consistent with previous research on the link between climate change and poverty (IPCC, 2022; Jafino et al., 2020; Noufé, 2020; Schleicher et al., 2018), which highlights the particular vulnerability of rural populations dependent on rain-fed agriculture.

These results underscore the urgency of implementing targeted public policies to strengthen the resilience of agricultural households. This includes developing flood protection infrastructure, promoting the adoption of drought-resilient crops, and improving access to climate risk management mechanisms such as agricultural insurance and early warning systems.

This study makes an important contribution to the understanding of how climate extremes affect rural poverty. However, it also has some limitations. The use of data from a single year does not allow us to capture the temporal dynamics of climate change, which is a gradual and multidimensional phenomenon. Future research would benefit from integrating longitudinal data over multiple years and expanding the analysis to other countries in the region for broader generalizability. Additionally, the use of alternative or complementary indicators of monetary and food poverty could enrich the analysis and better reflect the diversity of experiences among agricultural households.

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