VULNERABILITY TO DROUGHTS AND DETERMINANTS OF DIVERSIFICATION OF TEMPORARY CROPS IN NORTHEAST BRAZIL: A QUANTILE REGRESSION ANALYSIS

Vulnerabilidade a secas e determinantes da diversificação de culturas temporárias no Nordeste do Brasil: uma análise de regressão quantílica

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Abstract: This paper estimates the impacts of drought and identifies the determinants of diversification of temporary crops in the municipalities of Northeast Brazil. Using a quantile regression model with a fixed effects estimator, we find that diversification in rainfed agriculture increases with climate variability (climate change) but decreases with droughts. However, the impacts of droughts are smaller in areas with greater agricultural diversification. We also identify that family labor, conservation of natural resources, non-agricultural income, local market size, rainfall, access to rural credit, and subsistence farming are directly related to agricultural diversification, while mechanization, land use, temperature, dam construction, and business farming are inversely related. Taken together, these results support the recommendation of agricultural diversification policies to promote economic resilience, agrarian sustainability, and the adaptation of local farmers to climate change.

Keywords: agricultural diversification, droughts, climate change, semiarid, Northeast Brazil.

Resumo: Este artigo estima os impactos da seca e identifica os determinantes da diversificação de culturas temporárias nos municípios do Nordeste do Brasil. Usando um modelo de regressão quantílica com um estimador de efeitos fixos, descobrimos que a diversificação na agricultura de sequeiro aumenta com a variabilidade climática (mudança climática), mas diminui com as secas. Entretanto, os impactos das secas são menores em áreas com maior diversificação agrícola. Também identificamos que a mão de obra familiar, a conservação dos recursos naturais, a renda não agrícola, o tamanho do mercado local, as chuvas, o acesso ao crédito rural e a agricultura de subsistência estão diretamente relacionados à diversificação agrícola, enquanto a mecanização, o uso da terra, a temperatura, a construção de barragens e a agricultura empresarial estão inversamente relacionados. Em conjunto, esses resultados apoiam a recomendação de políticas de diversificação agrícola para promover a resiliência econômica, a sustentabilidade agrária e a adaptação dos agricultores locais às mudanças climáticas.

Palavras-chave: diversificação agrícola, secas, mudança climática, semiárido, Nordeste do Brasil.

Código JEL: Q15; Q18; Q54.

Recebido em: 30/05/2023
Aceito em: 22/01/2024

1 INTRODUCTION

Climate change will increasingly affect arid and semi-arid terrestrial ecosystems throughout this century. Climate projections suggest that these regions will become even drier and more frequently suffer from water stress (El-Beltagy; Madkour, 2012). Current and future scenarios reveal expressively challenges for the sustainable development of agriculture in semi-arid lands. In addition to being vulnerable to extreme events, such as droughts and floods, agriculture in these areas faces substantial constraints regarding the natural, financial, and technological resources needed to adapt to climate change and manage related risks (Singh; Chudasama, 2021).

The Northeast of Brazil is a semi-arid region often hit by extreme weather and increasingly exposed to climate change. Its vulnerability comes from geographic conditions, reliance on rainfed agriculture, and a large population of 57.6 million—the most populous semi-arid region worldwide. It produces 11% of Brazil's agricultural output and houses about 47.8% of the country's rural population involved in agriculture (Marengo et al., 2020)[1].

Droughts worsened by climate change reduce agricultural productivity and influence how land is used. Past droughts can change how farmers plan future crops, especially under ongoing climate risks, pests, and losses (Khanal; Mishra, 2017). This is especially true as droughts become more frequent. Farmers who grow temporary crops rely heavily on irregular rainfall. In semi-arid regions, poor water infrastructure and low soil quality make farming difficult, even in normal conditions (Zúñiga et al., 2021; Marengo et al., 2020). This has sparked debate over which farming systems best support sustainable agriculture in climate-vulnerable areas. Local farmers may adopt specialized, diversified, or hybrid systems[2].

This paper analyzes the impact of drought and the factors driving diversification of temporary crops in Northeast Brazil[3]. Using longitudinal data from 2000 to 2019, it tests the hypothesis that crop diversification has declined mainly due to intense, recurring droughts over the past two decades. It also examines whether climate variability prompts farmers to diversify more, indicating adaptation to worsening climate conditions[4].

Using a quantile regression model with fixed effects and natural variation in climate as a natural experiment, we estimate the causal effects of drought on agricultural diversification. Our main findings are: first, we document that diversification in rainfed agriculture increases with climatic variability but decreases with droughts. However, the impacts of droughts are smaller in areas with greater agricultural diversification, which is consistent with a process of municipal agriculture adaptation to adverse climatic conditions. Second, we identify that family labor, conservation

1 The increasing frequency of droughts has been causing growing damage to the agricultural sector in the Northeast. The damage caused by droughts to regional agriculture are estimated at up to R$ 1.5 billion per year (Marengo; Besnasconi, 2015).

2 A specialized system considers the use of land for the cultivation of high-yield crops and aims at economies of scale and technically efficient production (Sekyi et al., 2021). However, allocating agricultural land to some crops also brings disadvantages, such as the increased risk of crop losses and productivity and limitations in conventional sustainable management practices, such as crop rotation. This system is only viable in a stable market, requiring reliable commercial agencies and contracts. In regions where markets are still developing, the use of land for monoculture can reduce farmers' economic resilience to drought and negatively affect income and consumption levels (Birthal; Hazrana, 2019; Roest et al., 2018). Depending on the degree of risk aversion and resource scarcity, a diversified system with economies of scope can relatively reduce agricultural losses associated with droughts and, at the same time, contribute to sustainable agricultural development. Under these conditions, farmers have additional incentives to allocate land for polycultures. Incorporating hybrid and improved seeds into a diversified system is an important adaptation and resilience strategy for extreme climatic conditions. In addition, agricultural diversification increases soil fertility and food supply, leading to better nutrient absorption (Mulwa; Visser, 2020). In this context, farmers are increasingly trying to balance agricultural specialization and diversification to take advantage of the benefits of an intermediate system (Roest et al., 2018).

3 The study of the relationship between climate and diversification in rainfed agriculture is also a relevant issue in the Northeast, considering that out of the 1.64 million rural establishments that produce temporary crops, 81.2% are family farmers (Castro; Freitas, 2021). Previously, Seo (2010) found that South American farmers, including those in Brazil, prefer mixed cropping systems over specialized ones. This perspective provides additional context for our work.

4 Although there is a wide range of empirical evidence on the effects of climate shocks on agricultural production (e.g., Costa et al. (2021), Kuwayama et al. (2019), Birthal et al. (2019) and Deschênes and Greenstone (2007)); studies that explore the impacts of drought on agricultural land cover and use are still scarce (e.g., Rahman, 2016).

of natural resources, non-agricultural income, the size of the local market, precipitation, access to rural credit, and subsistence farming is directly related to the diversification of temporary crops in northeastern municipalities, while mechanization, land use, temperature, dam construction, and business farming are inversely related. Taken together, these results support the implementation of agricultural diversification policies to promote economic resilience, agrarian sustainability, and the adaptation of local farmers to climate change[5,6].

The remainder of the paper is organized as follows. In Section 2, we present the economic model that serves as a theoretical basis for analyzing the determinants and droughts in the diversification of rainfed agriculture. Section 3 presents the data and the econometric strategy. The empirical results are discussed in Section 4, and the conclusions are presented in the final section.

2 THE ECONOMIC MODEL

We expanded an economic model to analyze farmer's land use decisions for planting temporary crops in the context of climate change. The model builds on the theoretical and empirical frameworks of Smale et al. (2001), Benin et al. (2004), Isik (2004), and Rahman (2008, 2016). Our analysis assumes an economic setting where production and consumption take place simultaneously.

The farmer produces a vector Y of agricultural products using a vector of inputs M acquired in the input market. Their production choices are conditioned by the technology available to transform inputs into agricultural products that will be distributed in a consumer market, as well as the allocation of a fixed land area ($T = T^0$). This land is used for planting, given the characteristics of the property (Z). The total production of each farmer i is given by a stochastic quasi-concave production function:

$$Y_i = f\left(M_{ij1}, \ldots, M_{ijk}, \varepsilon \,\middle|\, T_i, Z_i\right), \quad \text{with } f_{M_k} > 0 \text{ and } f_{MM_k} < 0 \tag{1}$$

where ε is the stochastic variable that indicates a set of random factors that affect the level of agricultural production, including changes in weather conditions. The proportion of each planting area (α_j) among j temporary crops add up to one: $\sum_j^J \alpha_j = 1$, given $j = 1, 2, \ldots, J$, with mapping in the production vector. The proportion of the area planted with temporary crops determines the level of agricultural production (Rahman, 2016). The profit of each farm i is given by the following equation:

$$\pi_i(Y, M, p, \omega, \varepsilon \mid T_i, Z_i) = \sum_{j=1}^{J} p_j Y_{ij} - \sum_{k=1}^{K} \omega_j M_{ijk} \tag{2}$$

5 The results obtained in this study add new evidence to the literature investigating the impacts of climate change on agricultural diversification. Previous studies conducted by Rahman (2016), Piedra-Bonilla et al. (2020a), Makate et al. (2022), Birthal and Hazrana (2019), Mulwa and Visser (2020), and Bellon et al. (2020) have also examined this empirical issue in different contexts and regions of the world. However, some studies used cross-sectional data, while others focused on vulnerable regions. For example, Rahman (2016) concluded that precipitation increases agricultural diversification, while temperature variability reduces it in Bangladesh (South Asia). On the other hand, Makate et al. (2022) found that recurring droughts harm agricultural diversification in rural Ethiopia. As in these works, we arrived at conclusions that lead to the recommendation of agricultural diversification as a strategy for adapting to climate change.

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where p is the vector of agricultural product prices and ω is the vector of input prices.

It is assumed that the producer has a von Neumann-Morgenstern utility function, with $U(W)$ defining wealth. As the function is convex, then $U_W > 0$ and $U_{WW} < 0$. Accumulated wealth is given by the initial wealth (W_0) plus the profit (π_i) provided by agricultural production. According to Isik (2004) and Rahman (2016), the producer's objective is to maximize their expected utility function.

$$EU(W_0 + \pi_i(Y, M, p, \omega, \varepsilon | T_i, Z_i)) \tag{3}$$

Where E is the expectation operator defined over ε. The choice variables in Eq. (3) are the levels of inputs employed on the farm (M_{ijk}), characterized by the first-order conditions.

$$\frac{\partial EU}{\partial M_{ijk}} = EU_W \left(p_j \times f_{M_{ijk}} - \omega_k\right) = 0 \tag{4}$$

The second-order conditions are satisfied under risk aversion and an quasi-concave production function (Isik, 2004). We can rewrite Eq. (4) as follows:

$$E\left(p_j \times f_{M_{ijk}} - \omega_k\right) + \underbrace{\frac{Cov\left(U_W, f_{M_{ijk}}\right)}{EU_W}}_{\text{Risk Premium}} = 0 \tag{5}$$

where the covariance term is the marginal risk premium. A risk-averse farmer uses more (less) of an input with a negative (positive) marginal risk premium, given that the function is convex. The optimal levels of input and output are:

$$M^*_{ijk} = M^*_{ijk}\left(p_j, \omega_k, \varepsilon, U \mid T_i, Z_i\right) \tag{6}$$

$$Y^*_{ij} = f\left(M^*_{ij1}, \dots, M^*_{ijk}, \varepsilon \mid T_i, Z_i\right) \tag{7}$$

2.1 Determinants of diversification in rainfed agriculture

To identify the factors that influence farmers' choices regarding the planting of temporary crops, we derive the expected utility function, denoted by Eq. (3), following the approach of Benin et al. (2004) and Rahman (2008; 2016):

$$E_i = E[W_0 + \pi_i(Y, M, p, \omega, \varepsilon | T_i, Z_i)] \tag{8}$$

The equivalent income in a single decision-making period involves profits (π_i) from agricultural production and initial wealth orthogonal to agricultural crop choices (W_0), such as agricultural capital assets and other resources transferred from previous periods.

When markets function perfectly, households make agricultural production and consumption decisions separately. In this context, the household seeks to maximize farm profits, subject to technological and budget constraints. This decision-making process – such as crop selection –

can be expressed in a simplified form based on input and output prices, farm characteristics, land size, initial wealth, and the family's socioeconomic profile (Smale et al., 2001; Benin et al., 2004; Rahman, 2016).

$$h_i^* = h_i^*(p_j, \omega_k, Z_i, T_i, W_{oi}, \varepsilon_i) \tag{9}$$

Following Benin et al. (2004) and Rahman (2016), we use Equation (9) as the theoretical foundation for our empirical model. This equation is based on a constrained optimization problem and captures the main factors influencing land use decisions for planting. Given the local focus of this study, we extend the equation by introducing the term Υ to explicitly include additional variables such as market access, infrastructure, rural credit, natural resources, and municipal characteristics. The error term ε_i accounts for random influences like temperature and rainfall variability. In the Northeast region, producers and rural households' factor in the risk of drought when making production and consumption decisions. We treat droughts as random climate-related events and evaluate their impact on dryland agricultural diversification (El-Beltagy; Madkour, 2012). Our main assumption is that farmers' combined decisions – shaped by various influencing factors – reflect the local allocation of land for temporary crops in each period, as represented by the following equation:

$$S_{lt} = S_{lt}\left(\alpha_{ljt}^* \left(p_{lt}, \omega_{klt}, Z_{lt}, T_{lt}, W_{olt}, \Upsilon_{lt}, \varepsilon_{lt}\right)\right), \text{with } t = 2000, \ldots, 2019 \text{ and } l = 1, \ldots, 1794 \tag{10}$$

where S_{lt} represents the diversification index defined by the plot of land allocated for planting temporary crops (α_{ljt}^*, $j = 0, 1, \ldots, 33$) for l municipalities and t years. Moreover, this is also a measure of productivity, as farmers can increase output through agricultural specialization and diversification (Rahman, 2016).

3 DATA AND ECONOMETRIC STRATEGY

3.1 Data

Our empirical analysis is based on balanced panel data from 1,794 municipalities in Northeast Brazil, spanning 2000 to 2019. The dataset includes information on agricultural production, weather, natural resources, rural credit, water infrastructure, and sociodemographic conditions.

To evaluate the impact of drought on agricultural diversification, we used data from the *Produção Agrícola Municipal* (PAM) survey, which reports municipal-level information on the planted area of 33 temporary crops. From this, we calculated indicators of diversification in rainfed agriculture and created a variable to classify whether each municipality primarily grows business crops (corn) or subsistence crops (beans). Since soy was cultivated in only 2.2% of municipalities in the early 2000s, it was excluded from the business agriculture analysis. However, it's important to note the growing adoption of soy-corn double cropping systems in Brazil (Abrahão; Costa, 2018). These classification variables also reflect the influence of market demand on crop choices (Piedra-Bonilla et al., 2020).

We use weather data from the ERA5-Land database (ECMWF), which provides monthly temperature and precipitation records at a 9 km resolution from 1980 to 2019. These variables are used to calculate a drought index and measures of climate variability. Climate variability is measured by deviations in precipitation and temperature from long-term averages, capturing both drought and humidity conditions. The drought index calculation is detailed later.

Data on agricultural production factors were obtained from the 2006 and 2017 Agricultural Censuses. These include the number of tractors, family and non-family farmers, and the area of irrigated land. To account for changes over time, we weighted these factors by the area planted with temporary crops in each municipality. Irrigated land was weighted by the municipality's total area.

We sourced data on gross income, population, regional location, and land area from the *Instituto Brasileiro de Geografia e Estatística* (IBGE). From these, we calculated nonagricultural average income, population density, and agricultural land use. Data on rural credit stock came from the *Banco Central do Brasil* (BCB), which we used to create a variable for access to rural credit (Parré; Chagas, 2022). The *Secretaria do Tesouro Nacional* (STN) provided data on municipal agricultural spending, used to build a rural investment variable. Both rural credit and agricultural spending were weighted by the gross value of municipal production. All monetary values were adjusted to 2000 using the IGP-DI index.

We also included variables on natural resources and water infrastructure. Data from *Mapbiomas Brasil* were used to calculate forest and surface water coverage rates for each municipality. Information on water infrastructure comes from the *Portal da Transparência* (CGU), which reports municipalities with at least one completed contract for dam or weir construction, expansion, or implementation during the study period. This variable is binary, set to one if the municipality received such a project. Detailed variable descriptions and descriptive statistics are available in the Appendix (Tables A1–A3).

3.1.1 Agricultural diversification

To examine diversification in rainfed agriculture, we calculated the Simpson Diversity Index (S), which evaluates the contribution of each area planted with temporary crops to total cropland (Simpson, 1949). This index provides an indication of the spatial dispersion of temporary crop cultivation within a locality and can be derived as follows:

$$S_{lt} = 1 - \sum_{j=0}^{33} \alpha_{ljt}^2 , \; 0 \leq S_{lt} \leq 1, \text{ with } t = 2000, \dots, 2019 \text{ and } l = 1, \dots, 1794 \tag{11}$$

where S_{lt} is the Simpson Diversity Index (S) of rainfed agriculture for the municipalities (l) and year (t). α_{ljt} is the proportion of area planted with j temporary crops in the municipality (l) and year (t). A value of 0 represents perfect specialization, while a value of 1 denotes perfect diversification in municipal agriculture. Next, we calculated the untruncated version of the indicator: $MS_{lt} = \ln[1/(1 - S_{lt})]$. The modified index is the dependent variable in the empirical model.

As a measure of robustness, we also calculated the Shannon index (H) and the Effective Number of temporary crops planted (N) in each municipality. The indicators carry the structure of the Simpson index (S), that is, the proportion of the area planted with temporary crops (α_{ljt}). The Shannon index considers both the abundance and wealth, and uniformity of agricultural crops present in each municipality. In general, the index ranges from 1.5 to 3.5 (Parré; Chagas, 2022). The Shannon index is calculated as follows:

$$H' = - \sum_{i=1}^{n} \alpha_{jlt} \ln(\alpha_{jlt}), \text{with } \; H' \geq 0 \tag{12}$$

The Effective Number (N) is an agricultural diversification indicator derived from the Shannon index. The indicator informs the number of temporary crops that dominate rainfed agricultural production in each municipality in the Northeast Brazil The calculation of the indicator is carried out as follows (Aguilar et al., 2015):

$$N' = exp^{H'}, \text{with } N' \geq 0 \tag{13}$$

3.1.2 Standardized Drought Index

To measure extreme events, we calculate the Standardized Drought Index (SDI) using monthly precipitation and temperature data for Northeast Brazil from 1980 to 2019. The SDI combines above-normal temperatures and below-normal precipitation, capturing both heat and dryness to reflect drought severity (Yu; Babcock, 2010). The index is calculated using the following formula:

$$SDI_{lt} = \{-\min\left(0, TRD_{lt}^{sd}\right) \times \max\left(0, MTD_{lt}^{sd}\right)\} \tag{14}$$

where SDI_{lt} is the standardized drought index for the municipality (l) and year (t). TRD_{lt}^{sd} is the normalized deviation of seasonal precipitation relative to your normal value. MTD_{lt}^{sd} is the normalized deviation of seasonal temperature relative to your normal value. To make the index comparable across municipalities over time, the index is standardized. The statistical nature of this index gives it historical context and, because it is spatially consistent, allows comparisons between municipalities with markedly different climates.

3.2 ECONOMETRIC STRATEGY

3.2.1 Identifying determinants of agricultural diversification

Our econometric strategy first identifies the key factors driving diversification in rainfed agriculture. This exploratory analysis uncovers what promotes or limits agricultural diversification in Northeast Brazil, providing essential insights for policies and programs that support sustainable farming and climate resilience in municipalities. To do this, we use the following empirical model:

$$\begin{aligned} &MS_{lt} = \alpha + \mathrm{X'}_{\mathrm{lt}}\Gamma + FE_l + FE_t + \xi_{lt}, \\ &\text{with } t = 2000, \dots, 2019, \quad l = 1, \dots, 1794 \text{ and } u = 1, \dots, 9 \end{aligned} \tag{15}$$

where MS_{lt} is the Modified Simpson's diversification index for the municipality (l), state (u), and year (t), while X_{lt} is a vector of covariates: agricultural inputs, climatic conditions, natural resources, water infrastructure, type of cultivation, rural credit, rural investment, and characteristics of the municipality, such as market size (population density), average income non-rural, and land use with temporary crops. The municipality fixed effects () control for observable and unobservable time-invariant characteristics that influence agricultural planting decisions. Year fixed effects (FE_l) control shocks common to all municipalities in the region. The term Γ is a vector of parameters, and ξ_{lt} is the clustered error term at the local level.

We use the quantile regression via moments method proposed by Machado and Silva (2019), with fixed effects for municipalities and years, to examine how covariates affect agricultural diversification. The results from this method are consistent with those obtained using bidirectional fixed effects (Miao et al., 2022). We estimate the covariate effects locally, as well as at the 0.25 and 0.75 quantiles, to capture differences between municipalities with low and high levels of agricultural diversification.

3.2.2 Estimation the effect of drought on agricultural diversification

A natural experiment is essential to identify the causal effect of droughts on agricultural diversification. It allows us to construct a counterfactual-what would have happened in the absence of drought. To measure the impact of extreme events, we use a drought index based on the product of precipitation and temperature anomalies. This index provides exogenous variation, unrelated to farmers' decisions to plant temporary crops. Droughts serve as an ideal natural experiment because their timing, intensity, and duration are unpredictable. As a result, we can compare diversification levels across municipalities and isolate the causal effect of droughts without concerns about selection bias (Deschênes; Greenstone, 2007; Dell et al., 2014).

In this context, no other factors are expected to affect the relationship between droughts and agricultural diversification. If municipal-level diversification reflects the combined planting decisions of individual farmers – and based on the theoretical model – we estimate the causal effects using the following empirical equation:

$$MS_{lt} = \alpha + \sum_{k=0}^{2} SDI_{t-k}\beta_k + \mathrm{X'}_{\mathrm{lt}}\Gamma + FE_l + FE_s \times FE_t + \xi_{lt} \qquad (16)$$

where the drought index is denoted by SDI_{t-k} is our main measure of climate shocks at time $t-k$, with $k \epsilon \{0,1,2\}$, whose lags are calculated from 1998[7]. The coefficients β_k capture the contemporaneous and lagged effects of drought on agricultural diversification (MS_{lt}). The sum of the coefficients of interest ($\sum_{k=0}^{2} SDI_{t-k}\beta_k$) captures the contemporary and lagged effects of droughts on agricultural diversification. The lagged terms offer two direct advantages. First, they allow for accounting for the correlation of drought by discerning the possibility of temporal displacement of effects, resulting in one best estimation of the impact of contemporary shocks. Second, they enable the identification of the persistence of effects over the ongoing period. If weather effects are persistent, then the linear combination of contemporary and lagged coefficients (sum) must not be equal to zero. $\mathrm{X'}_{\mathrm{lt}}$ is a vector of control variables, such as agricultural inputs and municipal characteristics. In addition to the municipality fixed effects (FE_l), we also include a state and year fixed effects interaction $(FE_s \times FE_t)$ to control for common shocks that affect municipalities belonging to the same state.

The impact of droughts depends on their severity, duration, and the level of agricultural diversification (Seo, 2010). To test this, we use a quantile regression model to analyze how drought affects agricultural diversification across different levels in municipalities of Northeast Brazil.

4 RESULTS

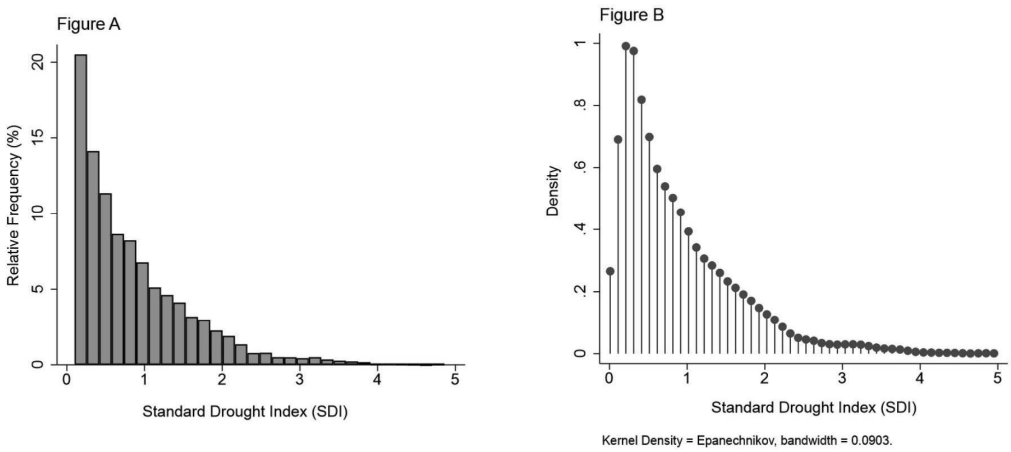
4.1 Drought events and diversification in rainfed agriculture

Figure 1 shows the distribution of the Standardized Drought Index (SDI) for Northeast Brazil from 2000 to 2019. The index ranges from 0 to 5, but we include only values above 0.1, following Yu and Babcock (2010). Values near 0.1 reflect normal precipitation and above-average tempera-

7 In the Appendix C, we present the results of the nonlinear effects of drought on agricultural diversification.

tures, indicating typical climate conditions. As shown, the SDI is concentrated near its lower limit, suggesting that most droughts in the period were of low or moderate intensity. Severe or extreme droughts (SDI > 1) were less frequent, as indicated by the kernel density.

Figure 1 – Frequency distribution and kernel density of the drought index



Notes: Relative frequency and kernel density considering the values of SDI > 0.1.

Table 1 shows the distribution of the SDI, the temperature and precipitation deviations used in its calculation, and the number of drought events by intensity for the periods 2000–2010 and 2010–2019. It also reports the average diversification indices in rainfed agriculture for each drought intensity level. Most droughts in Northeast Brazil between 2000 and 2010 were classified as mild (25.93%) or moderate (11.14%), while only 3% were extremely intense. On average, droughts were less severe during this decade, with a mean SDI of 0.532. Municipalities facing severe or extreme droughts showed greater agricultural diversification, cultivating an average of 3.3 temporary crops per year. In contrast, those affected by mild or moderate droughts had lower Simpson, Shannon, and Effective Number indices. Overall, the data suggest that more intense droughts are associated with higher levels of diversification in rainfed agriculture.

Table 1 – Distribution of the Standardized Drought Index (SDI) for Northeast Brazil

Severity level		SDI		Standardized deviation				Agricultural diversification			Drought Events	
				Min (TRD)		Max (MTD)		S	H	N		
Intensity	Scale	Mean	SD	Mean	SD	Mean	SD	Mean	Mean	Mean	N	%
Period 2000-2010												
Almost normal	SDI ≤ 0.1	0.005	0.017	0.087	0.197	0.104	0.230	0.540	1.001	2.895		
Light drought	SDI > 0.1 e SDI ≤ 0.5	0.267	0.114	0.499	0.237	0.590	0.227	0.547	1.006	2.911	2853	59.95
Moderate drought	SDI > 0.5 e SDI ≤ 1.0	0.723	0.147	0.785	0.195	0.957	0.227	0.545	1.008	2.902	1234	25.93
Severe drought	SDI > 1.0 e SDI ≤ 1.5	1.194	0.136	1.062	0.277	1.193	0.295	0.583	1.094	3.137	530	11.14
Extreme drought	SDI > 1.5	1.734	0.195	1.119	0.227	1.600	0.297	0.623	1.163	3.303	142	2.98
Mean	SDI> 0.1	0.532	0.400	0.654	0.312	0.783	0.354	0.553	1.021	2.946	4759	100
Period 2010-2019												
Almost normal	SDI ≤ 0.1	0.008	0.022	0.213	0.422	0.277	0.376	0.506	0.921	2.705		
Light drought	SDI > 0.1 e SDI ≤ 0.5	0.280	0.117	0.521	0.344	0.689	0.370	0.506	0.912	2.663	3276	32.15
Moderate drought	SDI > 0.5 e SDI ≤ 1.0	0.741	0.141	0.793	0.309	1.042	0.357	0.520	0.932	2.711	2752	27.01
Severe drought	SDI > 1.0 e SDI ≤ 1.5	1.243	0.147	1.011	0.290	1.314	0.351	0.511	0.919	2.687	1816	17.82
Extreme drought	SDI > 1.5	2.171	0.622	1.345	0.309	1.648	0.394	0.514	0.949	2.772	2345	23.02
Mean	SDI> 0.1	1.012	0.783	0.871	0.444	1.116	0.518	0.512	0.927	2.705	10189	100

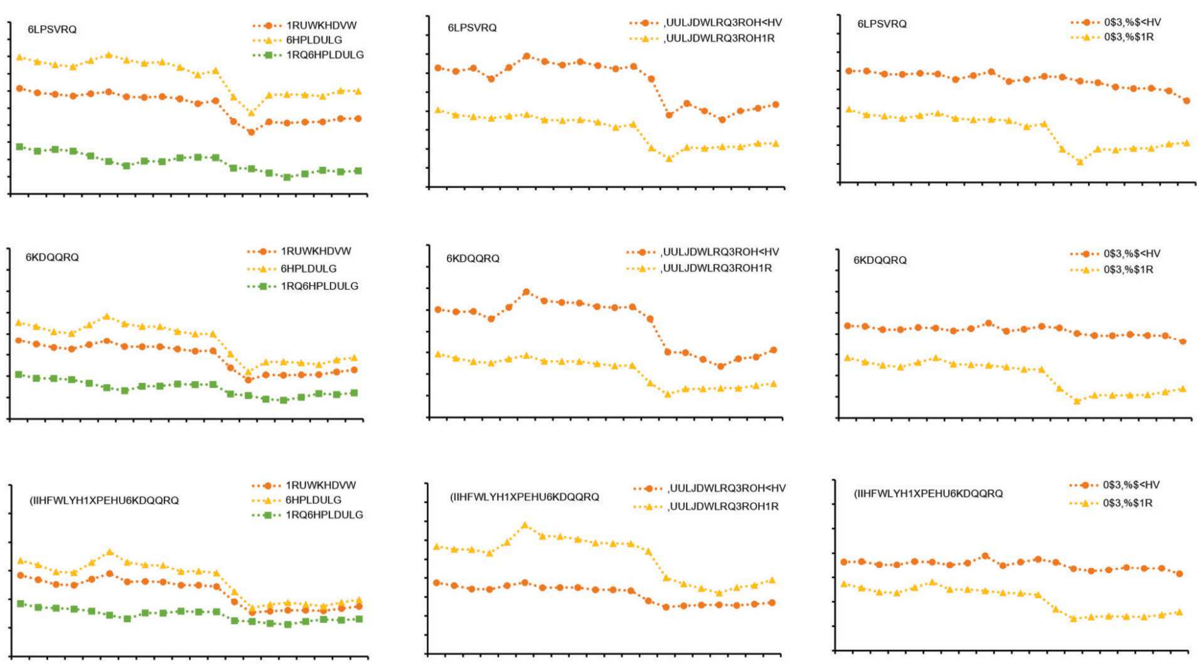
Notes: Standardized Drought Index (SDI) and standardized deviations for precipitation (TRD) and temperature (MTD). Indices of diversification in rainfed agriculture: Simpson (S), Shannon (H), and Effective Number (N). The intensity scale used is based on the scale developed by Birthal et al. (2015) and Yu and Babcock (2010) to determine drought intensity in India and the United States.

Between 2010 and 2019, Northeast Brazil faced its most severe drought in a century, with a sharp rise in moderate (27.01%), severe (17.82%), and extreme (23.02%) drought events. Compared to the previous decade, severe and extreme events increased significantly, and the average SDI nearly doubled to 1.012. At the same time, the Simpson and Shannon diversity indices fell by 7.4% and 9.2%, respectively. The average number of temporary crops in municipalities hit by extreme droughts dropped to 2.7. While these areas still showed relatively high diversification, the data point to a clear decline in crop diversity due to drought. This trend toward specialization threatens the long-term sustainability of the agricultural sector.

Figure 2 shows the evolution of rainfed agriculture diversification indices in Northeast Brazil from 2000 to 2019. The Simpson and Shannon indices rose steadily until 2010 but have declined since then across both semi-arid and non-semi-arid areas. Even in the MAPIBA region (Maranhão, Piauí, and Bahia)-the region’s new agricultural frontier-diversification has fallen. Despite the area's prominence in recent decades for its expanding grain production, driven by low land costs and corporate investment in agricultural technology, recurring droughts have also taken a toll.

Initial evidence points to a decline in agricultural diversification linked to the severe droughts since 2012. Between 2000 and 2019, diversification fell by about 8% according to the Simpson index, 10% by the Shannon index, and 9% by the Effective Number index. The Simpson index shows a decrease of 8.25% in the semi-arid region and 7.5% in the non-semi-arid region. In the MAPIBA area, diversification dropped by 6.7%, compared to 8.2% in non-MAPIBA areas. On average, agricultural diversification declined at a rate of 0.46% per year in the region, with annual reductions of 0.48% in the semi-arid zone and 0.42% in the non-semi-arid zone. The MAPIBA region saw an average yearly drop of 0.36%, while non-MAPIBA areas declined by 0.43% per year. Between 2000 and 2019, the effective number of temporary crops planted in the Northeast dropped from 2.9 to 2.6, reflecting similar declines in semi-arid areas (3.1 to 2.7) and non-semi--arid areas (2.7 to 2.5). This reduction in agricultural diversification also affects municipalities with publicly irrigated lands, where the Simpson and Shannon indices decrease annually by 0.4% and 0.63%, respectively. The number of temporary crops in irrigation hubs follows the same downward trend. The only exception is the MAPIBA area, where the average of three temporary crops has remained stable.

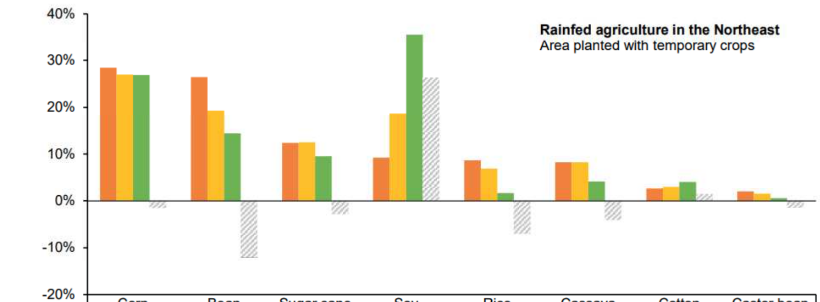
Figure 2 – Diversification of rainfed agriculture in Northeast Brazil, 2000-2019



Over the past two decades, the area for temporary crops in Northeast Brazil has changed significantly. Commercial crops like soybeans rose from 9.2% to 35.6%, and corn slightly increased from 28.4% to 26.9% of the planted area. Meanwhile, subsistence crops declined sharply: beans fell from 26.4% to 14.4%, and cassava from 8.2% to 4.1%. This shift toward commercial crops results from expanded grain cultivation in pasture and native vegetation areas and changes in the national agricultural export agenda. The drop in subsistence crops reflects the growth of commercial crops, shifting market demand, and frequent crop failures due to climate variability (Figure 3). However, this should not be seen as a simple replacement of subsistence crops by commercial ones, but rather as commercial crops increasingly dominating the total planted area. This concentration raises the risk of productivity and income losses, especially as climate change worsens droughts in the region.

Recent studies by Parré and Chagas (2022) and Piedra-Bonilla et al. (2020b) show a clear trend toward agricultural specialization across Brazil. This shift involves adopting cost-cutting technologies to meet rising demand for affordable food (Roest et al., 2018). However, the decline in agricultural diversification in the Northeast goes beyond economic and technological factors. Intense, recurring droughts create water shortages and lower crop yields, making it hard for farmers to maintain diverse crops sustainably (Makate et al., 2022; Marengo et al., 2020).

Figure 3 – Proportion of area planted with temporary crops in Northeast Brazil



	Corn	Bean	Sugar cane	Soy	Rice	Cassava	Cotton	Castor bean
2000	28.41%	26.43%	12.32%	9.21%	8.64%	8.21%	2.57%	1.99%
2010	26.94%	19.34%	12.45%	18.72%	6.88%	8.23%	2.99%	1.48%
2019	26.89%	14.37%	9.47%	35.56%	1.64%	4.12%	4.04%	0.53%
2000-2019	-1.52%	-12.06%	-2.85%	26.35%	-7.00%	-4.09%	1.47%	-1.46%

Figure 4 – Diversification of rainfed agriculture in the states of Northeast Brazil

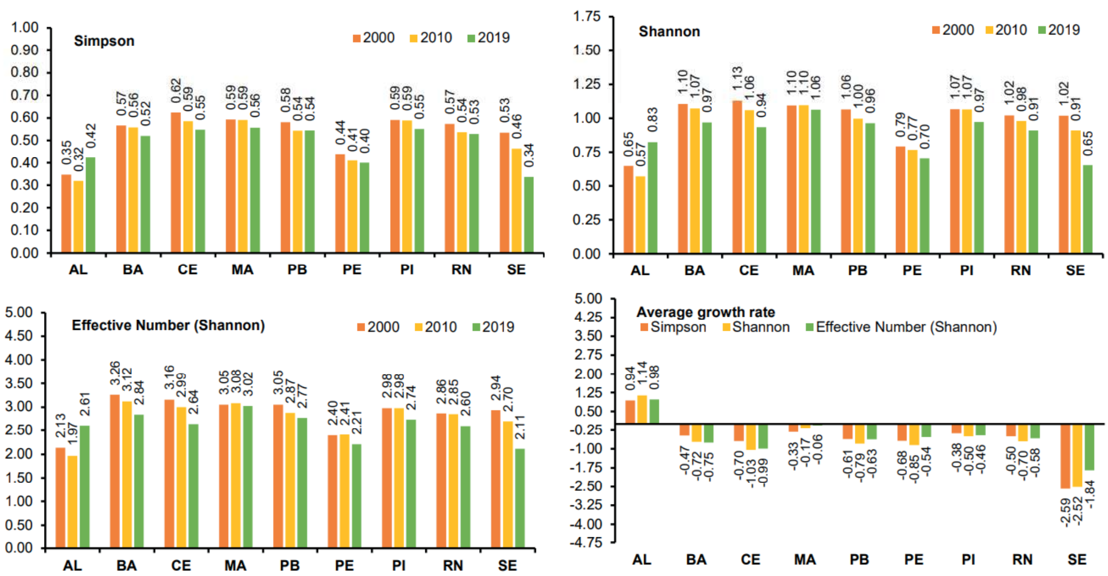
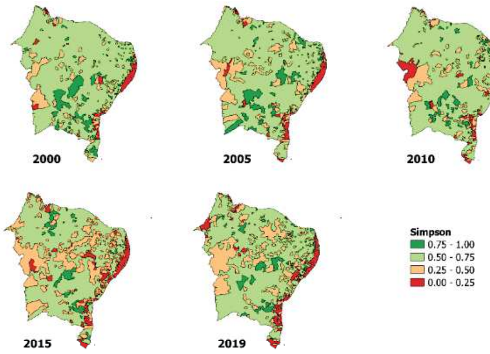


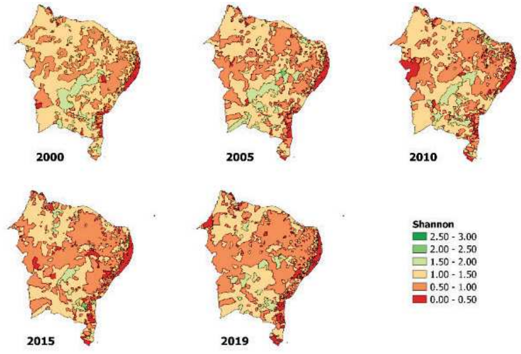
Figure 4 shows agricultural diversification in Northeast Brazil for 2000, 2010, and 2019. Except for Alagoas, which grew by 1% annually, all other states saw declines. Sergipe dropped 2.6% per year, while the rest fell between 0.3% and 1% annually. Maranhão stands out as the only state maintaining an average of three temporary crops per year; the others dropped to two.

Figure 5 shows the evolution of agricultural diversification from 2000 to 2019, with a five-year interval, using a color scheme where green indicates high agricultural diversification and red represents low diversification. The spatial distribution of the Simpson and Shannon indices reveals a trend of decreasing agricultural diversification in municipalities located in the central area of the Northeast region. This decline can likely be attributed to persistent water deficits and limited availability of natural resources. Consequently, this change in land cover increases the region's vulnerability to desertification and drought (Marengo et al., 2020).

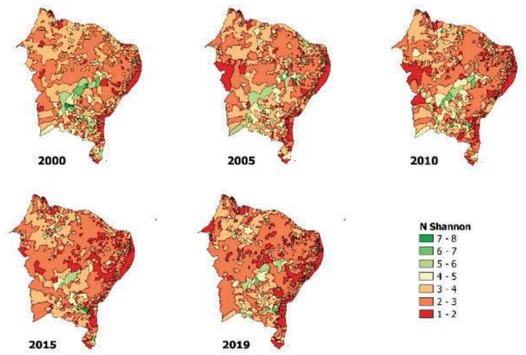
Figure 5 – Spatial distribution of agricultural diversification in Northeast Brazil



(A) Simpson Diversification



(B) Shannon Diversification



(C) Effective Number (N Shannon)

Notes: Simpson's index: highly diversified (1-0.75), diversified (0.75-0.50), specialized (0.50-0.25), and highly specialized (0.25-0).

Between 2000 and 2019, the Simpson index shows a drop in highly diversified municipalities from 5% to 4%, and diversified ones from 74% to 60%. Meanwhile, specialized municipalities rose from 13% to 24%, and highly specialized from 8% to 12%. In the semi-arid region, highly diversified municipalities fell from 6% to 4%, diversified from 83% to 68%, while specialized and highly specialized municipalities grew from 11% to 25% and 1% to 3%, respectively.[8]

The descriptive analysis aligns with studies worldwide. Aguilar et al. (2015) observed a decline in U.S. agricultural diversification driven by climate change, resource limits, and technological shifts, while regions that increased diversification adopted direct planting and crop rotation. Similarly, Makate et al. (2022) showed that drought shocks hindered diversification as a climate adaptation strategy in Ethiopia. Han and Lin (2021) reported mixed trends in China's regional agricultural diversification due to cyclical changes.

8 See the distribution of municipalities by level of agricultural diversification in the Appendix (Figure B1).

4.2 Analysis of the determinants of diversification in rainfed agriculture

Table 2 shows the results of the quantile regression model with fixed effects for municipality and year, applied to agricultural diversification indices. The Shannon and Effective Number indices confirm the robustness of the Simpson index results. The quantiles capture heterogeneous effects by examining covariate correlations at both low and high levels of agricultural diversification. These findings align with those from the bidirectional fixed effects model.

Precipitation boosts agricultural diversification measured by the Simpson and Shannon indices, while high temperatures reduce it – especially at the highest quantile. Elevated temperatures cause soil moisture deficits and water stress, lowering diversification at the municipal level. This significant effect matches Rahman's (2016) findings that year-round rainfall increases diversification in Bangladesh, whereas high temperatures decrease it.

Rainfall and temperature deviations (climate variability) are positively linked to agricultural diversification (Simpson and Shannon), especially in the lowest quantile. This shows that diversification in Northeast Brazil's municipalities increases with climate variability. Our findings align with Piedra-Bonilla et al. (2020a), who reported that irregular rainfall and temperatures boost diversification in Brazilian municipalities. However, their cross-sectional study, which combined temporary and permanent crops, could not separate effects by crop type. In short, climate variability drives diversification in rainfed cropping systems. Policymakers and practitioners aiming for sustainable agriculture in vulnerable regions should consider these impacts (□sfaw et al., 2018).

Lower levels of agricultural diversification are associated with greater land use and higher physical capital (Roest et al., 2018). The adoption of new technologies and mechanization tends to drive specialization. Physical capital has a significant impact only at low and medium diversification levels, while land use influences all levels. These findings are consistent with □nwer et al. (2019) and Birthal et al. (2020) for India, and Rahman (2008; 2016) for Bangladesh.

Family farmers drive diversification in dryland agriculture, boosting income, food security, and sustainability. In Northeast Brazil, rural families play a key role in food production for both local consumption and distribution. In contrast, non-family labor has mixed effects—reducing diversification at lower quantiles but increasing it at higher ones. Overall, the workforce is essential for enhancing productivity and agricultural diversity (Bellon et al., 2020; Herrera et al., 2018).

Irrigated land has no significant impact on agricultural diversification in the Northeast, a finding also reported by Rahman (2016) for Bangladesh. In contrast, diversification is positively linked to non-agricultural income, population density (as a proxy for market size), and rural credit. Higher income and larger markets drive diversification by increasing food demand. However, market size significantly affects only the effective number of crops. Similar patterns were found by □nwer et al. (2019) in India and Parré and Chagas (2022) in Brazil.

Rural credit significantly supports agricultural diversification across all quantiles. Investment credit enables the expansion of diversified systems, benefiting Northeast agriculture by reducing climate risks, production costs, greenhouse gas emissions, pests, and aiding soil conservation. This strategy should be combined with the cultivation of drought-tolerant crops and the adoption of environmentally sustainable practices (Piedra-Bonilla et al., 2020a).

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Table 2 – Quantile regression via moments for determinants of diversification in rainfed agriculture

	Modified Simpson			**Shannon**			**Effective Number**		
	0.25	**Local**	**0.75**	**0.25**	**Local**	**0.75**	**0.25**	**Local**	**0.75**
Land use (soil)	**-0.171*****	**-0.140*****	**-0.110*****	**-0.216*****	**-0.189*****	**-0.164*****	**-0.790*****	**-0.678*****	**-0.574*****
	[0.0280]	[0.0294]	[0.0343]	[0.0314]	[0.0305]	[0.0337]	[0.105]	[0.115]	[0.138]
Capital (tractors)	**-0.0263*****	**-0.00970****	0.00619	**-0.0409*****	**-0.0226*****	-0.00554	**-0.101*****	**-0.0371****	0.0233
	[0.00403]	[0.00396]	[0.00449]	[0.00455]	[0.00387]	[0.00388]	[0.0148]	[0.0153]	[0.0180]
Family work	**0.0229*****	**0.0187*****	**0.0147*****	**0.0345*****	**0.0257*****	**0.0174*****	**0.0789*****	**0.0635*****	**0.0491*****
	[0.00410]	[0.00362]	[0.00385]	[0.00503]	[0.00393]	[0.00365]	[0.0150]	[0.0138]	[0.0153]
Non-family work	-0.00536	0.00147	**0.00802****	**-0.00926*****	-0.0016	**0.00558***	-0.0167	0.0102	**0.0355****
	[0.00337]	[0.00325]	[0.00378]	[0.00350]	[0.00303]	[0.00315]	[0.0123]	[0.0124]	[0.0148]
Irrigated area	0.00391	0.00327	0.00266	0.00374	0.00293	0.00216	0.013	0.0153	0.0174
	[0.00258]	[0.00255]	[0.00300]	[0.00283]	[0.00252]	[0.00272]	[0.00927]	[0.00989]	[0.0122]
Rainfall	**0.102*****	**0.0836*****	**0.0656*****	**0.0831*****	**0.0666*****	**0.0510*****	**0.360*****	**0.337*****	**0.316*****
	[0.0173]	[0.0154]	[0.0160]	[0.0177]	[0.0138]	[0.0123]	[0.0670]	[0.0617]	[0.0666]
Rainfall deviation	**0.0114*****	**0.00776****	0.00429	0.00645	0.00453	0.00272	**0.0343****	**0.0342****	**0.0340****
	[0.00404]	[0.00359]	[0.00383]	[0.00404]	[0.00320]	[0.00299]	[0.0153]	[0.0142]	[0.0157]
Temperature	-0.221	**-0.941****	**-1.632*****	0.207	-0.356	**-0.885*****	**-2.576***	**-4.992*****	**-7.259*****
	[0.404]	[0.378]	[0.419]	[0.361]	[0.313]	[0.324]	[1.549]	[1.494]	[1.698]
Temperature deviation	**0.0143****	**0.0272*****	**0.0395*****	0.00575	**0.0166*****	**0.0268*****	**0.0792*****	**0.130*****	**0.177*****
	[0.00687]	[0.00645]	[0.00725]	[0.00625]	[0.00542]	[0.00567]	[0.0262]	[0.0254]	[0.0295]
Rural credit	**0.00213****	**0.00268****	**0.00320*****	**0.00266*****	**0.00272*****	**0.00277*****	**0.00962****	**0.0121*****	**0.0145*****
	[0.00108]	[0.00105]	[0.00120]	[0.000980]	[0.000863]	[0.000905]	[0.00408]	[0.00417]	[0.00493]
Average income	0.0105	**0.0154***	**0.0201****	**0.0193****	**0.0182****	**0.0171****	0.051	**0.0780****	**0.103*****
	[0.00954]	[0.00914]	[0.00975]	[0.00921]	[0.00780]	[0.00748]	[0.0361]	[0.0355]	[0.0393]
Market size (Density)	0.00949	0.0271	0.044	0.0233	0.0241	0.0248	0.0491	0.156	**0.257****
	[0.0297]	[0.0280]	[0.0297]	[0.0306]	[0.0258]	[0.0243]	[0.119]	[0.118]	[0.129]
Rural investment	0.000814	0.000213	-0.000363	0.000826	0.00045	0.0000977	0.00315	0.00131	-0.000417
	[0.000882]	[0.000847]	[0.000972]	[0.000870]	[0.000740]	[0.000768]	[0.00336]	[0.00336]	[0.00395]
Forest coverage	**0.0201***	0.0164	0.0129	0.0164	0.0145	0.0126	**0.0752***	0.0607	0.0471
	[0.0111]	[0.0104]	[0.0114]	[0.0104]	[0.00893]	[0.00903]	[0.0420]	[0.0417]	[0.0475]
Water resource	-0.0001	**0.00362***	**0.00716*****	**0.00350***	**0.00540*****	**0.00717*****	0.007	**0.0199****	**0.0320*****
	[0.00201]	[0.00196]	[0.00215]	[0.00186]	[0.00158]	[0.00157]	[0.00770]	[0.00778]	[0.00874]
Weir	0.0143	0.00039	-0.0129	0.0145	0.00687	-0.000249	0.0576	0.0115	-0.0317
	[0.0131]	[0.0131]	[0.0150]	[0.00977]	[0.00880]	[0.00943]	[0.0532]	[0.0602]	[0.0738]
Dam	**-0.0305***	**-0.0316***	**-0.0327***	-0.0142	-0.0142	-0.0143	-0.112	-0.126	-0.14
	[0.0179]	[0.0171]	[0.0177]	[0.0127]	[0.0110]	[0.0103]	[0.0738]	[0.0780]	[0.0869]
Commercial cultivation (corn)	**0.0324*****	0.00275	**-0.0257*****	**0.0387*****	**0.0142*****	**-0.00889****	-0.0117	**-0.0975*****	**-0.178*****
	[0.00555]	[0.00507]	[0.00539]	[0.00493]	[0.00392]	[0.00353]	[0.0201]	[0.0195]	[0.0215]
Subsistence cultivation (beans)	**0.114*****	**0.0753*****	**0.0379*****	**0.0908*****	**0.0569*****	**0.0252*****	**0.247*****	**0.135*****	0.0299
	[0.00630]	[0.00601]	[0.00668]	[0.00564]	[0.00461]	[0.00450]	[0.0226]	[0.0226]	[0.0260]

Notes: Dependent variable is an index of agricultural diversification in natural logarithm. Result of quantile regression with moments estimator and fixed effects of municipalities and year. The local result corresponds to the standard estimation with bidirectional fixed effects. The statistical multicollinearity test (VIF) yielded an average value of 1.92 for each model. Invariant variables such as labor, tractors, and irrigated area are weighted by temporary crop areas to vary over time. Corn and bean cultivation are binary variables that take the value of one if the municipality has a cultivation area above the mean within the regional cultivation area. In brackets are the grouped standard errors at the local level, robust to heteroscedasticity and autocorrelation. Significant *** 1%, ** 5%, and * 10%.

Water availability is positively linked to greater agricultural diversification, while the presence of infrastructure like dams shows a negative correlation. Supporting water conservation is essential, as it promotes sustainable agricultural practices and reduces climate-related risks. In contrast, building dams tends to discourage diversification as a strategy for managing agricultural risk (Marengo et al., 2022; Birthal; Hazrana, 2019).

Land use focused on commercial crops like corn is linked to lower agricultural diversification (Shannon and Effective Number). In contrast, bean cultivation boosts diversification, showing that subsistence farming promotes more diverse agricultural systems in municipalities (Roest et al., 2018).

4.3 Effects of drought on diversification of rainfed agriculture

Table 3 – Effects of drought on diversification of rainfed agriculture

	Modified Simpson		Shannon		Effective Number	
	(1)	(2)	(3)	(4)	(5)	(6)
SDI, t	**-0.0131*****	**-0.0124*****	**-0.0145*****	**-0.0129*****	**-0.0613*****	**-0.0581*****
	[0.00320]	[0.00320]	[0.00288]	[0.00286]	[0.0121]	[0.0121]
SDI, t–1	**-0.0170*****	**-0.0177*****	**-0.0167*****	**-0.0166*****	**-0.0823*****	**-0.0849*****
	[0.00338]	[0.00331]	[0.00307]	[0.00296]	[0.0127]	[0.0124]
SDI, t–2	**-0.00593****	**-0.00522***	**-0.00470****	**-0.00352**	**-0.0419*****	**-0.0380*****
	[0.00280]	[0.00280]	[0.00236]	[0.00236]	[0.0111]	[0.0110]
Sum (SDI)	**-0.0361*****	**-0.0353*****	**-0.0359*****	**-0.0330*****	**-0.186*****	**-0.181*****
	[0.00764]	[0.00758]	[0.0068]	[0.0067]	[0.0299]	[0.0296]
Var. dependent (mean)	1.200	1.200	0.654	0.654	2.808	2.808
SD within (SDI, t)	0.609	0.609	0.609	0.609	0.609	0.609
R–sq	0.077	0.095	0.124	0.156	0.102	0.122
Test F (3, 1793)	**9.17*****	**9.88*****	**11.88*****	**11.80*****	**14.54*****	**15.72*****
N	35,880	35,880	35,880	35,880	35,880	35,880
Fixed effect: municipal	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effect: state x year	Yes	Yes	Yes	Yes	Yes	Yes
Basic controls	No	Yes	No	Yes	No	Yes

Notes: Dependent variable is an index of agricultural diversification in natural logarithm. In brackets are the grouped standard errors at the local level, robust to heteroscedasticity and autocorrelation. Significant *** 1%, ** 5%, and * 10%.

Table 3 shows the effects of drought on diversification in rainfed agriculture, both with and without controls. The F-statistics are significant at the 1% level across all models, confirming that the contemporaneous and lagged coefficients of the Standardized Drought Index (SDI) are jointly significant. Controlling for agricultural inputs and municipal characteristics unrelated to drought does not affect the results, which remain robust and statistically significant for all diversification indicators – Simpson, Shannon, and Effective Number. The inclusion of these covariates does not significantly alter the coefficients or standard errors, suggesting that the SDI behaves like a random variable across municipalities in the Northeast.

Model analysis with controls shows that cumulative drought reduces diversification of temporary crop areas by 3% (Simpson), 5.5% (Shannon), and 6.5% (Effective Number) compared to the unconditional average. This indicates that ongoing drought—caused by combined rainfall and temperature variations—significantly lowers municipal agricultural diversification in terms of quantity, abundance, and equity. Specifically, a one standard deviation increase in the current drought index decreases diversification by 0.75% (Simpson), 0.79% (Shannon), and 3.54% (Effective Number) (Table 4). These results are consistent with Costa et al. (2021), which found that temporary crop production in Brazil's semiarid region is highly vulnerable to drought shocks.

Quantile regression results (Table 4) show that drought impacts agricultural diversification unevenly, hitting areas with low diversification hardest. Municipalities with less diversified temporary crops are less resilient to drought, while those with higher diversification are more resistant. This supports the idea that diversification is a key strategy for managing climate risks in rainfed agriculture (Birthal; Hazrana, 2019).

A one-standard-deviation rise in the current drought index reduces Simpson's diversification index by 1.2% at the 0.1 quantile and 0.3% at the 0.9 quantile. The Shannon index shows a similar pattern, with drought lowering diversification by 1.5% at the 0.1 quantile and 0.1% at the 0.9 quantile. However, the drought impact at the 0.9 quantile is statistically insignificant for both indices. Effects on the Effective Number of temporary crops follow the same trend. These findings align with Seo (2010), who reported that diversified cropping systems suffer less climate damage than specialized ones in hot, dry conditions – though both are negatively affected by climate shocks.

A one-standard-deviation increase in contemporary drought reduces agricultural diversification by 0.8% in both Simpson and Shannon indices and by 3.5% in the Effective Number. Higher diversification levels lessen the immediate and one-year lagged drought impacts. However, when drought lasts over a year, its negative effect grows. After two years, drought damages increase even in highly diversified areas, likely because managing multiple crops becomes harder during prolonged dry spells (Seo, 2010).

Table 4 – Effects of drought on diversification of rainfed agriculture

	Quantiles of agricultural diversification									
	0.1		**0.25**		**Local**		**0.75**		**0.9**	
	Quantile	**Impact**	**Quantile**	**Impact**	**Quantile**	**Impact**	**Quantile**	**Impact**	**Quantile**	**Impact**
Modified Simpson										
SDI, t	**-0.0192*** **	**-1.2%**	**-0.0162*** **	**-1.0%**	**-0.0124*** **	**-0.8%**	**-0.00856*** **	**-0.5%**	-0.00566	-0.3%
	[0.00442]		[0.00375]		[0.00320]		[0.00319]		[0.00355]	
SDI, t–1	**-0.0248*** **	**-1.4%**	**-0.0217*** **	**-1.2%**	**-0.0177*** **	**-1.0%**	**-0.0138*** **	**-0.8%**	**-0.0108*** **	**-0.6%**
	[0.00487]		[0.00401]		[0.00330]		[0.00333]		[0.00384]	
SDI, t–2	-0.0025	-0.2%	-0.00368	-0.3%	**-0.00522***	**-0.4%**	**-0.00673****	**-0.5%**	**-0.00788****	**-0.6%**
	[0.00373]		[0.00314]		[0.00279]		[0.00304]		[0.00356]	
Shannon										
SDI, t	**-0.0253*** **	**-1.5%**	**-0.0195*** **	**-1.2%**	**-0.0129*** **	**-0.8%**	**-0.00635****	**-0.4%**	-0.0017	-0.1%
	[0.00453]		[0.00366]		[0.00286]		[0.00251]		[0.00265]	
SDI, t–1	**-0.0272*** **	**-1.5%**	**-0.0223*** **	**-1.2%**	**-0.0166*** **	**-0.9%**	**-0.0111*** **	**-0.6%**	**-0.00711****	**-0.4%**
	[0.00499]		[0.00391]		[0.00295]		[0.00264]		[0.00294]	
SDI, t–2	-0.00204	-0.2%	-0.00273	-0.2%	-0.00352	-0.3%	**-0.00429***	**-0.3%**	**-0.00484***	**-0.4%**
	[0.00357]		[0.00288]		[0.00236]		[0.00230]		[0.00256]	
Effective Number										
SDI, t	**-0.0862*** **	**-5.2%**	**-0.0749*** **	**-4.6%**	**-0.0581*** **	**-3.5%**	**-0.0417*** **	**-2.5%**	**-0.0280***	**-1.7%**
	[0.0153]		[0.0135]		[0.0121]		[0.0129]		[0.0150]	
SDI, t–1	**-0.108*** **	**-6.1%**	**-0.0987*** **	**-5.5%**	**-0.0849*** **	**-4.8%**	**-0.0714*** **	**-4.0%**	**-0.0602*** **	**-3.4%**
	[0.0163]		[0.0140]		[0.0124]		[0.0135]		[0.0161]	
SDI, t–2	**-0.0247***	**-1.8%**	**-0.0301****	**-2.2%**	**-0.0380*** **	**-2.8%**	**-0.0458*** **	**-3.4%**	**-0.0523*** **	**-3.9%**
	[0.0136]		[0.0118]		[0.0110]		[0.0125]		[0.0149]	

Notes: Dependent variable is an index of agricultural diversification in natural logarithm. Estimation of quantile regression model via moments with fixed effects of the municipality and state-year and control variables. The heterogeneous effects of drought on agricultural diversification are calculated using the standard deviation (within) for the drought index: SDI, t (0.609), SDI, t-1 (0.560), and SDI, t-2 (0.736). In brackets are the grouped standard errors at the local level, robust to heteroscedasticity and autocorrelation. Significant *** 1%, ** 5%, and * 10%.

Table 5 shows the non-linear effects of drought on agricultural diversification. The local impact of a current drought shock is similar to the linear estimates: 0.8% for Simpson, 0.93% for Shannon, and 3.16% for Effective Number. However, drought shocks at lower levels exert a greater influence on reducing agricultural diversification, while at higher levels, the contemporary impact is statistically insignificant. In contrast, lagged drought shocks significantly affect areas with higher diversification. This indicates that growing a variety of temporary crops helps buffer drought effects lasting up to a year. As droughts persist, diversification drops sharply, especially in municipalities with less variety. Thus, agricultural diversification acts as an adaptive strategy that boosts resilience against prolonged droughts.

Our results show that agriculture in Northeast Brazil is becoming more vulnerable to climate change, mainly due to drought-driven reductions in agricultural diversification. This highlights the urgent need for climate risk management policies and incentives to promote diversified farming systems. Supporting diversification in rainfed agriculture not only lessens drought impacts but also safeguards incomes, boosts food security, and preserves local biodiversity (Zúñiga et al., 2021; Mulwa; Visser, 2020; Makate et al., 2022; Bellon et al., 2020). Expanding rural services and improving access to credit can help municipalities diversify agriculture, optimize scarce natural resources, and strengthen small farmers' economic resilience. Additionally, local governments can support diversification by investing in targeted public programs, such as expanding technical assistance and providing improved seeds to smallholders (Piedra-Bonilla et al., 2020a; Roest et al., 2018; Seo, 2010).

Table 5 – Effect of drought shocks on agricultural diversification

	Quantiles of agricultural diversification									
	0.10		**0.25**		**Local**		**0.75**		**0.90**	
	Quantile	**Impact**	**Quantile**	**Impact**	**Quantile**	**Impact**	**Quantile**	**Impact**	**Quantile**	**Impact**
Modified Simpson										
Drought shock, t	**-0.0226*** **	**-2.3%**	**-0.0162*** **	**-1.62%**	**-0.00791***	**-0.79%**	0.000254	0.03%	0.0065	0.65%
	[0.00619]		[0.00516]		[0.00446]		[0.00481]		[0.00567]	
Drought shock, t–1	**-0.0329*** **	**-3.3%**	**-0.0288*** **	**-2.88%**	**-0.0235*** **	**-2.35%**	**-0.0182*** **	**-1.82%**	**-0.0142*** **	**-1.42%**
	[0.00628]		[0.00523]		[0.00444]		[0.00464]		**[0.00541]**	
Drought shock, t–2	-0.0044	-0.4%	-0.00654	-0.65%	**-0.00936****	**-0.94%**	**-0.0121*** **	**-1.21%**	**-0.0142*** **	**-1.42%**
	[0.00519]		[0.00430]		[0.00375]		[0.00412]		[0.00490]	
Shannon										
Drought shock, t	**-0.0229*** **	**-2.29%**	**-0.0165*** **	**-1.65%**	**-0.00929****	**-0.93%**	-0.00217	-0.22%	0.00293	0.29%
	[0.00623]		[0.00490]		[0.00385]		[0.00368]		[0.00419]	
Drought shock, t–1	**-0.0321*** **	**-3.21%**	**-0.0268*** **	**-2.68%**	**-0.0209*** **	**-2.09%**	**-0.0150*** **	**-1.50%**	**-0.0107*** **	**-1.07%**
	[0.00651]		[0.00510]		[0.00392]		[0.00360]		[0.00403]	
Drought shock, t–2	-0.000121	-0.01%	-0.00243	-0.24%	**-0.00502***	**-0.50%**	**-0.00758*** **	**-0.76%**	**-0.00942*** **	**-0.94%**
	[0.00497]		[0.00387]		[0.00302]		[0.00292]		[0.00335]	
Effective Number										
Drought shock, t	**-0.0827*** **	**-8.27%**	**-0.0622*** **	**-6.22%**	**-0.0316***	**-3.16%**	-0.00174	-0.17%	0.023	2.30%
	[0.0211]		[0.0183]		[0.0170]		[0.0196]		[0.0239]	
Drought shock, t–1	**-0.128*** **	**-12.80%**	**-0.116*** **	**-11.60%**	**-0.0969*** **	**-9.69%**	**-0.0785*** **	**-7.85%**	**-0.0632*** **	**-6.32%**
	[0.0212]		[0.0183]		[0.0168]		[0.0189]		[0.0229]	
Drought shock, t–2	**-0.0323***	**-3.23%**	**-0.0395****	**-3.95%**	**-0.0503*** **	**-5.03%**	**-0.0608*** **	**-6.08%**	**-0.0695*** **	**-6.95%**
	[0.0187]		[0.0161]		[0.0149]		[0.0172]		[0.0210]	

Notes: Dependent variable is an index of agricultural diversification in natural logarithm. Drought shock when the SDI > 1.5. In brackets are the grouped standard errors at the local level, robust to heteroscedasticity and autocorrelation. Estimation of quantile regression model via moments with fixed effects of the municipality and state-year and control variables. Significant *** 1%, ** 5%, and * 10%.

Robustness check. Appendix C shows robustness checks using both linear and non-linear drought measures: (i) different SDI intensity bins (Table C.1); (ii) separate effects of precipitation and temperature deviations as drought indicators (Table C.2); and (iii) SDI in contemporary, quadratic, and cubic forms (Table C.3).

We can summarize these additional results as follows. First, the results confirm the robustness and consistency of the results presented in this section. Examining the nonlinear effects, we find that the more severe the drought, the greater the decrease in agricultural diversification. This effect is more pronounced in municipalities that are more specialized in planting temporary crops. In addition, temperature deviations in the form of drought contribute more to the decline in agricultural diversification, although the decrease in precipitation has the same effect. This is consistent with evidence that higher temperatures negatively affect the diversification of temporary crops due to their sensitivity to thermal stress and changes in growth cycles, as well as the increased risk of pests and diseases. Furthermore, contemporary SDI has a negative effect on agricultural diversification, while square and cubic SDI have positive and negative effects, respectively. Intuitively, this implies that droughts can promote both increased and decreased agricultural diversification in Northeast Brazil.

5 FINAL REMARKS

Diversifying temporary crops offers major benefits for food security, environmental protection, and sustainable farming. This is especially important in Brazil's Northeast, where frequent droughts and a strong reliance on agriculture make the region highly vulnerable. By adopting crop diversification, local farmers can better withstand climate change, boost productivity, and strengthen their economic resilience – all while preserving natural resources.

Given the projected increase in drought frequency and intensity due to climate change, we analyzed how these events affect the diversification of land used for temporary crops in the Brazilian Northeast. Our findings show that over 60% of municipalities have satisfactory levels of diversification-68% in semi-arid areas and 46% in non-semiarid areas. However, agricultural diversification has declined steadily over the past two decades, averaging a 0.5% drop per year. From 2000 to 2019, diversification in rainfed agriculture fell by 8% across the Northeast-8.25% in the semi-arid region and 7.5% in the non-semiarid region. This decline is largely driven by climate change, which has intensified recurring droughts. It's important to note that regional changes in crop diversification don't necessarily reflect changes in the number of rural establishments.

Our results show that while climate variability is linked to increased agricultural diversification, droughts have the opposite effect, reducing the variety of temporary crops planted in Northeast municipalities. These impacts vary across regions and are strongest where diversification is already low. As droughts become more frequent and prolonged, the risks to income and productivity grow, making it essential for farmers and local governments to adopt adaptation strategies to reduce these risks.

Our analysis shows that agricultural diversification in municipalities tends to increase with factors like family labor, natural resource conservation (water and forests), local market size, non-rural income, rainfall, and access to rural credit. In contrast, diversification decreases with greater mechanization, intensive use of land for temporary crops, higher temperatures, and dam construction. We also find that higher diversification in rainfed agriculture is linked to subsistence farming, while lower diversification is associated with commercial crop cultivation. Growing high-yield crops like corn often leads to reduced agricultural diversification.

Our findings support the promotion of rural credit policies focused on sustainable production, as they give farmers the financial means to adopt new crops and modernize farming practices. These actions are key to diversifying local agricultural production, securing small farmers' livelihoods, and boosting sustainability and resilience to drought. Other necessary measures include expanding technical assistance and increasing public investment to support family farming, which plays a vital role in diversification, food security, and sustainable development.

Given the impact of drought on crop failure and productivity – with consequences such as food insecurity and rural poverty – our results offer valuable guidance for public policies aimed at climate adaptation in semi-arid regions of the developing world. We show that diversifying temporary crops can strengthen economic resilience and help reduce agricultural losses in Brazil's Northeast.

ACKNOWLEDGEMENTS

This research was conducted with the support of the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES). The authors thank CAPES and UFJF for the financial and institutional support granted to carry out this study.

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