

# Climate change and family farming in Brazil: regional impacts by productivity quantiles

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## Abstract

Family farming in Brazil, significant in social, economic, and environmental terms, is characterized by productive heterogeneity, particularly at the regional level. Climate change, also spatially heterogeneous, influences agricultural productivity. Farmers with higher productivity, due to better control over the production process, tend to be less affected by climate changes. In this context, this study analyzes the impacts of climate change on different quantiles of land productivity in family farming across Brazil's federal units and macro-regions. The methodology encompasses a micro-founded theoretical model that guides the cross-sectional estimation of a quantile regression of land productivity, considering climatic, geographic, and productive factors. The results indicate that the intensity of the negative effects of climate change would be more pronounced in the lower productivity quantiles and in the North, Northeast, and Southeast regions, highlighting that the climatic phenomenon could exacerbate the vulnerability of the most fragile producers and regional disparities. The study uses the average agricultural productivity of a set of crops relevant in economic terms, which generalizes the results. Future advances include the disaggregation of projections by individual crops. The results point to negatively affected regions, which can be used by policy makers in the context of climate change adaptation policies. The work is an original contribution to the literature on the impacts of climate change on family farming productivity. It presents a pioneering approach to regionally analyzing the effects on productivity among different types of family farmers in Brazil, a group that accounts for 77% of the country's agricultural producers.

**Keywords:** Family farming; Climate Change; Productive heterogeneity; Climate heterogeneity; vulnerability;

**JEL Code:** Q1, Q13, Q54

## 1. Introduction

The advent of climate change, evidenced by changes in temperature and precipitation, directly affects agricultural productivity and, consequently, the income generated by producers. Projections by INPE (Chou et al., 2017) on precipitation and temperature patterns highlight the spatial heterogeneity of this phenomenon across Brazil. In this context, a new agricultural geography of production is expected (Pinto et al., 2008; Assad et al., 2016). Nevertheless, the Brazilian agricultural sector is also highly heterogeneous among producers and regions, indicating that the effects of climate change on productivity may exhibit differentiated dynamics depending on the producer's profile (Tanure et al., 2024; De Paula, 2020).

Family farming plays an important role in the current production system from social, economic and environmental perspectives. According to the Agricultural Census IBGE (2017), family farming

accounts for a significant share of national production in crops such as cassava, tobacco, coffee, beans, bananas, and grapes. Its importance is further underscored by its role in preserving local cultures and traditions, protecting ecosystems, and enhancing food accessibility.

According to FAO (2014), family farming (FF) is defined as a way to ensure agricultural and forestry production, as well as fishing and herding, managed and operated by a family that mostly depends on non-salaried family labor, involving both women and men. The family and the farm are interconnected, co-evolving and combining economic, environmental, reproductive, social, and cultural functions.

In organizational terms, family farming is distinctly structured compared to corporate farming. In FF, labor and management are closely intertwined, production is diversified with a strong reliance on internal input use, decision-making processes are immediate, pluriactivity and complementary wage labor are evident, and producers exhibit varying levels of mechanization, education, and market integration among producers (Veiga, 1996; Schneider, 2003; Escher et al., 2014).

This last aspect is regionally evident in Brazil. Producers in the South, Southeast, and Midwest regions demonstrate stronger market integration, higher participation in PRONAF, and greater use of technical assistance, which allows for greater control over agricultural productivity. In contrast, family producers in the North and Northeast regions are more vulnerable, with subsistence production being predominant.

The literature addressing the impacts of climate change on agricultural productivity, while extensive, seldom explores farmers' productive heterogeneity and predominantly focuses on high-value commodities. Globally, the effects on agriculture vary. In mid- and high-latitude regions, moderate temperature increases, coupled with higher CO<sub>2</sub> concentrations and changes in precipitation patterns, are expected to enhance crop yields. However, in arid regions and low-latitude areas, production is expected to decline (Lobell et al., 2008; Hitz & Smith, 2004; FAO, 2003; 2005; NRC, 2012).

For Brazil, projections by Assad et al. (2013) indicate a reduction in agricultural suitability for crops such as rice, coffee, beans, sunflower, corn, and soybeans. Regionally, Feres et al. (2011) forecast reduced profitability in the North, Northeast, and Midwest regions, while the South and Southeast are expected to experience increased profitability. Assunção and Chein (2016) estimate an 18% reduction in agricultural productivity per hectare nationwide, with municipal-level effects ranging from -40% to +15%, with the most significant negative impacts concentrated in the North, Northeast, and Midwest.

Considering productive specificities, De Paula (2020) provides evidence that the productive structure plays a crucial role in shaping the effects of climate change on agricultural productivity and, consequently, on land prices. For instance, a 1°C increase in average temperature results in a 5% reduction in average land prices for more productive farmers in the South region, whereas less productive farmers in the North experience a significantly greater reduction of 34%.

Specific studies on the impacts of climate change on family farming productivity remain scarce. Tanure *et al.*, (2024) estimate higher sensitivity of family farming land productivity to climatic effects compared to large-scale farming. Greater control over the production process in large-scale farming, via soil treatment, irrigation, and technical assistance, helps mitigate the negative impacts of climate on productivity. Spatially, the study identifies negative productivity impacts in the North and Northeast, moderate effects in the Southeast and Midwest, and positive impacts in the South. These regional variations further emphasize the productive heterogeneity of family farming in Brazil

Therefore, considering that the productive structure shapes the sensitivity of productivity to climate change and that significant productive heterogeneity exists even within family farming, it is essential to examine how climate change affects different profiles of family farmers. Moreover, the concentration of negative effects in regions dominated by subsistence family farming may further exacerbate the vulnerability of the most fragile producers. This study offers an innovative approach by analyzing the impacts of climate change on distinct family farmer profiles, incorporating their regional productive specificities as well as climatic heterogeneity.

To conduct the analysis, this study adopts a theoretical model guiding the cross-sectional estimation of a quantile regression of agricultural productivity, incorporating climatic, geographic, and productive factors. This methodology enables the assessment of climate change impacts under the RCP 4.5 and RCP 8.5 scenarios on producers with varying land productivity profiles. To capture productive heterogeneity, the analysis segments family farmers into quantiles representing low, medium, and high productivity groups, by federal unit and macro-region of Brazil, allowing for the identification of the most vulnerable producers and regions.

The study is structured into five sections, including this introduction. Section 2 outlines the materials and methods, describing the theoretical model that informs the quantile regression estimation and presenting the dataset used. Section 3 reports the estimation results by macro-region of Brazil. Section 4 provides a discussion of the findings. Finally, the concluding section summarizes the study's main contributions.

## 2. Material and Methods

The microeconomic theoretical model underpinning the econometric exercise is based on the studies of Assunção and Chein (2016) and Tanure *et al.*, (2024), in which land allocation is determined by productive, climatic and geographical factors. The model considers an agricultural economy composed of  $M$  municipalities, where each municipality  $m \in M$  has a representative farmer who allocates land  $T_m$  among  $K$  different crops. The production  $P_{mk}$  of crop  $k \in K$  in municipality  $m \in M$  depends on the amount of land  $T_{mk}$  and inputs  $I_{mk}$  allocated to this crop, as well as a vector with climatic and geographic characteristics  $CG_m$ :

$$P_{mk}(CG_m) = \gamma_{mk} f^k(L_{mk}, I_{mk} | CG_m) \quad (1)$$

$\gamma_{mk}$  is an individual productivity vector and  $f_T^k > 0$ ,  $f_I^k > 0$ ,  $f_{TT}^k \leq 0$  e  $f_{II}^k \leq 0$ .

Considering  $w_m$  the unit price of inputs, the representative farmer's decision problem can be divided into two stages. In the first stages, the farmer selects the optimal quantity of inputs to maximize the profit derived from the production of crop  $k$  in municipality  $m$  for each given value of  $T_{mk}$ . The value function for this problem is defined as:

$$V_{mk}(T_{mk} | GC_m) = \max_{X_{mk}} [\gamma_{mk} f^k(T_{mk}, I_{mk} | GC_m) - w_m I_{mk}] \quad (2)$$

In the second stage, the representative farmer determines the optimal land allocation to maximize aggregate returns, subject to the constraint of available land:

$$\max_{\{L_{mk}\}} \Pi_m(CG_m) = \sum_k V_{mk}(T_{mk} | CG_m), \text{ sujeito a } \sum_k T_{mk} = T_m \quad (3)$$

The first-order conditions of the problem (3) are given by:

$$V'_{mk}(T_{mk}|CG_m) \geq V'_{mk}(T_{mk}|CG_m), \forall k, k' > 0 \in K \quad (4)$$

Equation (4) will be valid as equality whenever  $T_{mk}^* > 0$  and will be valid as strict inequality whenever  $T_{mk}^* = 0$ .

The equilibrium of the model is given by the following equality:

$$\sum_k T_{mk}^*(CG_m) = T_m \quad (5)$$

Equations (4) and (5) illustrate how climate change in  $GC_m$  influence producers' decision-making, particularly in terms of agricultural productivity, implicitly defining the optimal land allocation. If the vector with the climatic characteristics shifts from  $GC_m$  to  $CG_m$ , the marginal value of the different agricultural activities will be affected heterogeneously. Thus, the land allocation  $T_{mk}^*(CG'_m)$  will differ from the initial allocation of land  $T_{mk}^*(CG_m)$ , as farmers adjust their crop choices in response to changing profitability due to climate change.

Climate change in  $CG_m$  generates two key effects: first, a direct impact on agricultural productivity, and second, a shift in land use resulting from productivity changes. Thus, the model captures farmers' adaptive responses to climate change in terms of land allocation.

By defining an agricultural productivity vector as a measure of land productivity per crop – i.e., a measure of partial productivity,  $\gamma_m = (\gamma_{m1}, \gamma_{m2}, \dots, \gamma_{mk})$ , and solving the system of equations (4) and (5) while incorporating the production function defined in equation (1), we can express the equilibrium agricultural productivity of each crop as a function of the model's parameters:

$$Y_{mk}^*(CG_m) = \frac{P_{mk}^*(CG_m)}{T_{mk}^*(CG_m)} = Y_k(w_m, \gamma_m, CG_m) \quad (6)$$

From equation (6), aggregate agricultural productivity can be defined as the ratio between the total value of production and the harvested area, measured in hectares. The production value, expressed in reais (R\$), accounts for the price of each crop in its respective unit – kilograms, tons or bags – per hectare, enabling the calculation of aggregate productivity:

$$Y_m^*(CG_m) = \frac{P_m^*(CG_m)}{T_m^*(CG_m)} = Y(w_m, \gamma_m, CG_m) \quad (7)$$

Equations (6) and (7), which define agricultural productivity, serve as the foundation for the empirical analysis conducted in the next section. These equations enable the estimation of how family farming productivity quartiles respond to climatic factors.

## 2.1 Econometric specification and estimation

The estimation of the impacts of climate change on agricultural productivity was based on the studies of Assunção and Chein (2016), Barbosa *et al.*, (2020) and Tanure *et al.*, (2023). However, this study introduces an innovation by employing quantile regression to capture the effects of climate on different productivity quantiles of family farming. Quantile regression offers a more robust alternative to the ordinary least squares estimation (OLS), which focuses solely on conditional mean. This approach enables the analysis of variations in the distribution and its shape by examining different quantiles or segments of the conditional distribution (Koenker and Bassett Jr, 1978; Buchinsky, 1998). This feature is particularly valuable for analyses involving family farming, where productive heterogeneity leads to an asymmetric distribution of land productivity, especially at the regional level.

The sensitivity of agricultural productivity to climate change effects for crop  $k$  in municipality  $m$  is determined by equation (6). Suppose that there is perfect mobility of productive factors across the municipalities in the sample. This assumption implies that factor prices are identical across all municipalities ( $w = w_m, \forall m$ ), allowing the model to be estimated without factor pricing data. The functional form describing the relationship between climatic factors and productivity is given by:

$$Y_m = Y(w, \gamma_m, CG_m) = \exp[\theta(CG_m) + \gamma_m + \epsilon_m] \quad (8)$$

Where  $\epsilon_m$  represents an idiosyncratic error term. Rewriting (8), we obtain:

$$\ln Y_m = \gamma_m + \theta(CG_m) + \epsilon_m \quad (9)$$

The approximation of municipal characteristics  $\gamma_m$ , without the use of panel data, is conducted through the observable characteristics  $X_m$ . Thus, the following estimable equation is obtained:

$$\ln Y_m = \theta(CG_m) + \beta' X_m + \epsilon_m \quad (10)$$

From equation (10), the conditional quantile functions of  $\ln Y_m$  are given by:

$$Q_\tau(\ln Y_m | x) = \theta(CG_m)\tau + \beta' X_m \tau + F_\epsilon^{-1}(\tau) \quad (11)$$

Where  $\tau$  represents the  $t$ -th quantile and denotes the common distribution function of the errors. The estimation is performed using the 0.25, 0.50 and 0.75 quantiles. After estimating the model represented in equation (11), the average temperature and precipitation variables ( $GC_m$ ) are replaced, in the same model, by their projected values ( $GC'_m$ ) under RCP 4.5 and RCP 8.5 scenarios, while all other control variables remain unchanged. Subsequently, the predicted value of  $\ln Y_m$  is calculated for each quantile.

$$\ln Y_m = \theta(CG'_m) + \beta' X_m + \epsilon_m \quad (11)$$

The variation in land productivity resulting from climatic variables is given by the difference determined as follows:

$$\Delta \ln Y_m = [\theta(CG_m) + \beta X_m] - [\theta(CG'_m) + \beta X_m] \quad (12)$$

Thus, let  $Y_{m0}$  represent the land productivity when  $CG_m = CG_{m0}$ , and  $Y_{m1}$  represent the land productivity when  $CG_m = CG_{m1}$ . The impact of climate change is then given by  $\Delta Y^* = Y^*_{m1} - Y^*_{m0}$ .

Initial increases in temperature and precipitation may enhance productivity; however, excessive increases (e.g., extreme temperature or precipitation levels) may hinder it. To account for the nonlinearity of these effects, the estimation includes a quadratic polynomial for temperature and precipitation (Mendelsohn *et al.*, 1994; Feres *et al.*, 2009).

As climatic variables, the quarterly averages of temperature and precipitation were used, corresponding to the seasons – spring, summer, autumn, and winter – in order to capture the specific effects of climatic seasonality on the agricultural productivity of each crop. Finally, to calculate aggregate land productivity, a weighting scheme based on the square root of the total agricultural area of each municipality was applied (Schlenker *et al.*, 2006).

It is important to emphasize that in the projections, the model does not incorporate new productive technologies as an adaptive strategy of farmers. This a crucial aspect to consider in studies

analysing the impacts of climate change – that is, the estimated model does not account for technological progress. Therefore, the results should be understood as the pure effect of climate on productivity, highlighting the magnitude of the technological advancements required to mitigate the effects of climate change on land productivity (Assunção and Chein, 2016).

## 2.2 Database

The model utilized a sample of 4,693 municipalities for estimating the climatic impacts on agricultural land productivity. Municipalities with missing data on land use or climatic variables were excluded from the econometric analysis. The database used in this study was sourced from the 2017 Agricultural Census conducted by IBGE. Sixteen family farming crops were selected for analysis: banana, coffee, orange, pineapple, peanuts, rice, English potato, sugarcane, beans, tobacco, cassava, corn, soybean, wheat, other temporary crops, and other permanent crops.

To determine agricultural productivity, a partial land productivity measure was employed. The number of hectares cultivated with crop  $k$  in each municipality  $m$  defines the land use for each crop category. The productivity of crop  $k$  in municipality  $m$  is calculated as the ratio of the production value to the cultivated area of  $k$  in  $m$ :

$$Y_{mk} = \frac{\text{Production value of } k \text{ in } m}{\text{Cultivated land area of } k \text{ in } m}$$

Aggregate land productivity is defined as:

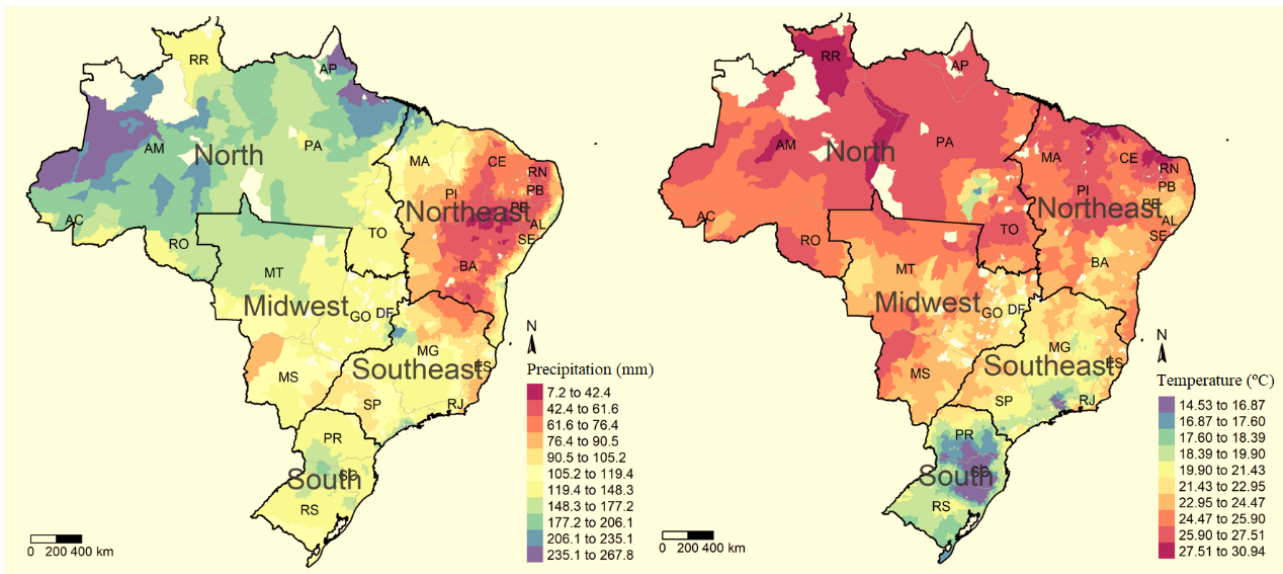
$$Y_m = \frac{\sum_k \text{Production value of } k \text{ in } m}{\text{Cultivated land area in } m}$$

The control variables used in the empirical analysis were sourced from the 2017 Agricultural Census and relate to the factors employed in production. These variables include: i) Natural Logarithm of Machinery Value, as the natural logarithm of the value of machinery, equipment, and tractors available on properties, per hectare; ii) Labor Intensity – the natural logarithm of the number of workers per hectare; iii) Improved area – the area occupied by buildings, improvements or pathways; iv) Irrigated Area – measured in hectares; v) Soil pH Correction Participation – the percentage of establishments that applied soil pH correction.; vi) Predominant Soil Type – categorical classification of soil characteristics; vii) geographic variables – altitude, latitude and longitude, at the municipal level, extracted from Ipeadata database.

The climatic data used to estimate monthly average temperature and precipitation for the baseline scenario model were sourced from the Terrestrial Air Temperature and Precipitation database, as described by Matsuura and Wilmott (2012). The temporal scope for constructing the baseline model corresponds to a climatological normal<sup>1</sup> period of 34 years, from 1971 to 2005. Figure 2 presents historical municipal-level data for average temperature and precipitation across Brazil, providing a spatial representation of these climatic factors.

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<sup>1</sup> The World Meteorological Organization (WMO) establishes a minimum standard of thirty years for climate change analysis. This period, known as climatological normal, serves as reference for calculating the average values of climatic variables. Climate change is identified when significant variations occur in the average values of these variables between different climatological normal periods.

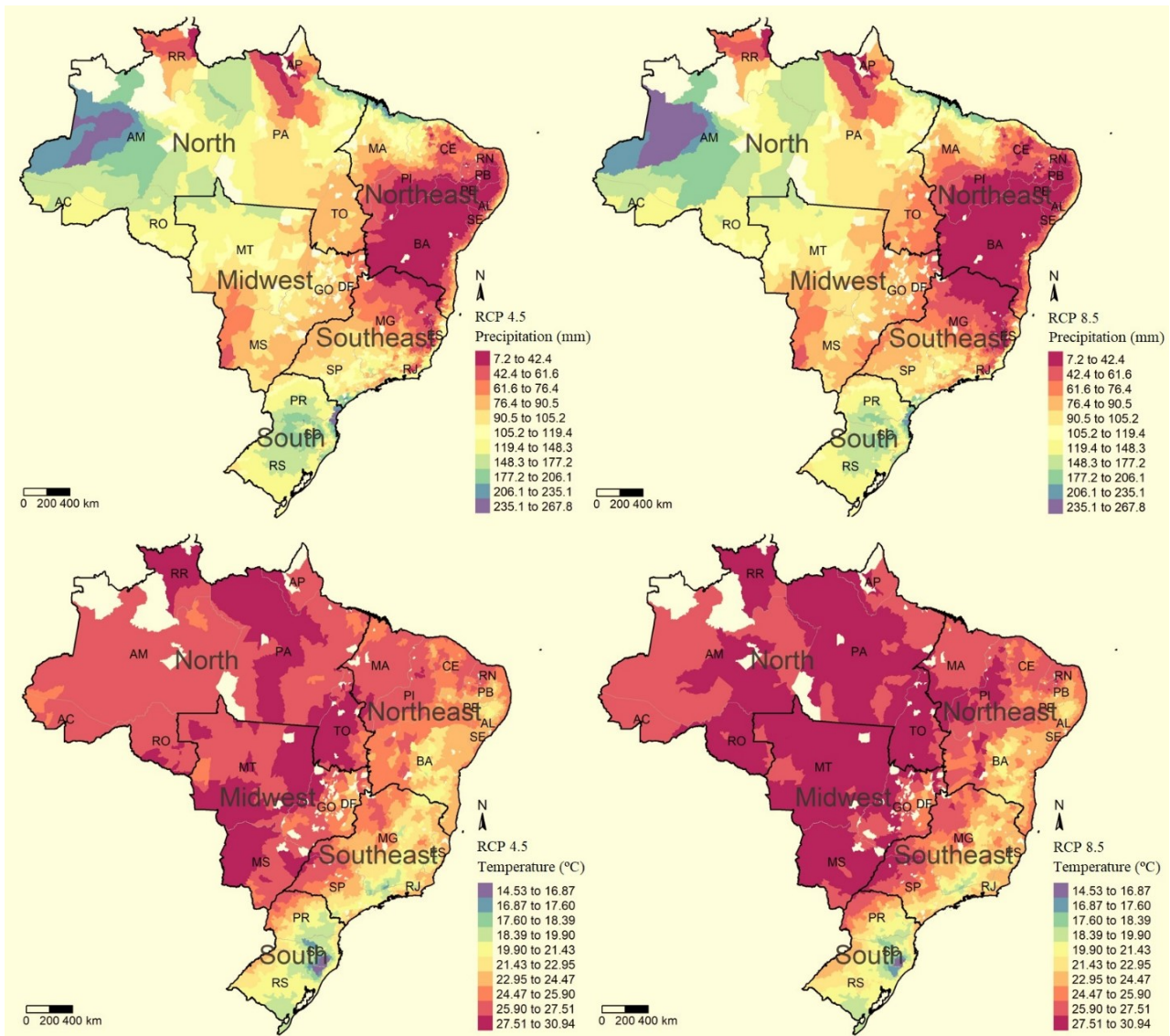


**Figure 1: Historical Precipitation and Temperature Data (1971-2005) (mm) (°C)**

Source: Prepared by the authors based on Matsuura and Willmott (2012)

The projected temperature and precipitation data used in the estimated model correspond to the RCP 4.5 and RCP 8.5 scenarios from the IPCC (2014), covering the period from 2021 to 2050. The climate projections for Brazil, developed by INPE and based on the 1971-2005 climatological normal, were generated using the Eta-CPTEC regional climate model (Chou *et al.*, 2014).

The RCP 4.5 scenario represents a more optimistic trajectory for global greenhouse gas (GHG) emissions and temperature evolution, projecting an average global warming of 1.8°C by 2100, relative to the 1986-2005 baseline. Conversely, the RCP 8.5 scenario represents a pessimistic pathway, with a projected global warming of approximately 3.7°C by 2100 (IPCC, 2014). Figures 3 and 4 illustrate the precipitation and temperature projections for the respective climate scenarios.



**Figure 2: Precipitation and Average Temperature Projected by RCP 4.5 and RCP 8.5 (mm) (°C) Scenarios**

Source: Prepared by the authors based on Chou *et al.* (2014)

The temperature projections for the year 2050 under the RCP 4.5 and RCP 8.5 scenarios indicate a more intense increase in low-latitude regions and the central portion of Brazil. In this context, the North, Northeast, and Midwest regions are expected to experience the greatest impacts, particularly under the RCP 8.5 scenario. Regarding precipitation, compared to the historical scenario (Figure 1), the projected scenarios indicate a significant reduction in precipitation levels, with a more severe decline under the RCP 8.5 scenario. The Northeast region is expected to be the most affected.

### 3. Results and Discussion

To project the impacts of climate change on family farming land productivity, while accounting for rodutive specificities and spatial climatic heterogeneity, this study first estimated a baseline model represented by equation (11). In this model, aggregate land productivity of family farming is

estimated based on productive, geographic, and climatic variables, employing quantile regression to capture the lower (0.25), median (0.50), and upper (0.75) quantiles of land productivity.

The climatic variables used in the analysis include quarterly averages of temperature and precipitation between the years 1975 and 2005. Thus, the baseline model indicates how productive, geographic, and historical climatic factors influence family farming land productivity. Table 1 presents the results of the baseline model.

**Table 1 – Baseline Model Estimation**

Control Variables	Dependent Variable: log (Total Agricultural Productivity)		
	.25 (bottom quartile)	.50 (median)	.75 (top quartile)
Temperature Spring	0.182 (0.194)	-0.158 (0.255)	-0.632* (0.371)
Temperature Summer	-1.599*** (0.233)	-1.453*** (0.371)	-1.225** (0.507)
Temperature Autumn	1.211*** (0.144)	0.815*** (0.191)	0.672** (0.266)
Temperature Winter	-0.623*** (0.103)	-0.211 (0.148)	-0.0127 (0.212)
Temp. Spring^2	-0.0106*** (0.004)	-0.00323 (0.00519)	0.00611 (0.00764)
Summer Season^2	0.0361*** (0.004)	0.0337*** (0.00753)	0.0304*** (0.0104)
Autumn Season^2	-0.0261*** (0.003)	-0.0174*** (0.00434)	-0.0127** (0.00631)
Winter Temp^2	0.0163*** (0.002)	0.00676** (0.00323)	0.000859 (0.00492)
Spring Precipitation	0.0124*** (0.0008)	0.0126*** (0.000792)	0.0105*** (0.00114)
Precipitation Summer	0.00437*** (0.0009)	0.00538*** (0.000841)	0.00695*** (0.00114)
Autumn Precipitation	-0.00724*** (0.0009)	-0.0106*** (0.00106)	-0.0131*** (0.00122)
Winter Precipitation	0.00725*** (0.00137)	0.0141*** (0.00151)	0.0183*** (0.00168)
Prec. Spring^2	-0.0000331*** (0.000002)	-0.0000360*** (0.00000197)	-0.0000315*** (0.00000377)
Prec. Summer^2	-0.00000854*** (0.000002)	-0.00000972*** (0.00000186)	-0.0000128*** (0.00000236)
Prec. Autumn^2	0.0000275*** (0.000002)	0.0000303*** (0.00000257)	0.0000354*** (0.00000265)
Prec. Winter^2	-0.0000270*** (0.000005)	-0.0000506*** (0.00000563)	-0.0000721*** (0.00000546)
Altitude	-0.000391*** (0.00004)	-0.000411*** (0.0000535)	-0.000253*** (0.0000755)
Latitude	0.00598 (0.00672)	0.0122** (0.00582)	0.0184** (0.00775)
Longitude	-0.0104*** (0.00370)	-0.0133*** (0.00283)	-0.0202*** (0.00393)
Capital	0.0536*** (0.00814)	0.0140 (0.00863)	0.00546 (0.0109)
Labor	0.165***	0.197***	0.179***

	(0.0152)	(0.0159)	(0.0191)
Improvements	0.0000271*** (0.000005)	0.0000220*** (0.00000183)	0.0000172** (0.00000793)
Irrigation	0.0000118*** (0.000002)	0.00000987*** (0.000000725)	0.0000135 (0.0000271)
pH soil correction	0.583*** (0.0643)	0.803*** (0.0746)	0.837*** (0.0908)
Soil Type	-0.0190*** (0.002)	-0.0154*** (0.00255)	-0.00571* (0.00326)
Constant	17.65*** (1.346)	19.78*** (2.024)	21.51*** (2.725)
Pseudo R-Square	0.4241	0.3334	0.2844

Source: Prepared by the authors based on the results of the econometric model. Note: Robust standard error to heteroscedasticity in parentheses. p-value <0.01, \*\* p-value <0.05, \* p-value <0.1.

The results of the baseline model estimation indicate that most control variables were statistically significant, particularly the climatic variables, whose effects varied across different productivity quantiles. This variation underscores that climate, along with geographic and productive factors, influences different profiles of family farmers in distinct ways. This distinction is evident in the varying magnitudes of impact across land productivity quantiles.

Increases in temperature during summer and winter area associated with a decline in land productivity for all producers, with the reduction being more pronounced among lower-productivity farmers. Conversely, temperature increases in autumn lead to higher productivity, with a more significant effect on lower-productivity farmers. These findings suggest that temperature effects on productivity are more substantial for producers with lower productivity levels.

The spring temperature variable and its quadratic term were the only variables to exhibit differing signs across productivity quantiles. The results indicate that a one-degree Celsius increase in the average spring temperature would lead to a 0.18% increase in productivity for farmers in the lower productivity quantile. However, the same temperature increase would result in a 0.15% reduction in productivity for the median quantile and a 0.62% reduction for farmers in the upper productivity quantile.

Regarding precipitation, higher-productivity producers were found to be more sensitive to changes. Increased precipitation during winter and summer is associated to productivity gains, with a more pronounced effect among higher-productivity farmers. However, higher precipitation levels in autumn would result in productivity declines, with a greater impact on higher-productivity producers. This pattern of effects is the opposite of that observed for temperature variables.

The productive control variables demonstrated high levels of significance and exhibited expected signs. Labor, capital, improvements, irrigation, and soil pH correction all had positive signs, indicating a positive correlation between their use and productivity levels. The labor and capital variables follow the expected pattern across productivity profiles, with lower-productivity farmers relying more on labor-intensive practices, while higher-productivity farmers exhibited greater capital intensity.

In this context, the results indicate that increases in labor have a greater impact on the productivity of higher-productivity farmers, while increases in capital have a more substantial effect on the productivity of lower-productivity farmers.

### 3.1 Results by Federation Units

Based on the baseline model results, which demonstrate the effects of climate on land productivity, we projected the impacts of climate change on family farming land productivity by productivity quantile. Using equation (11), we replaced the historical climatic variables for precipitation and temperature with the projected averages provided by INPE, according to the RCP 4.5 and RCP 8.5 scenarios, for the period 2021-2050. Keeping the estimated coefficients and other control variables constant, we calculated a new productivity level. Equation (12) was then applied to compute the productivity variation between the baseline model and the model incorporating climate projections. The reported values represent averages weighted by the production area in municipalities, assigning greater weight to larger areas in determining the region's aggregate productivity. The results can be interpreted as the pure effect of climate on land productivity.

The projected outcomes reflect both spatial climatic and productive heterogeneity of family farmers. As a result, the impacts vary across regions and among different productivity profiles of family farmers. Overall, the results indicate more severe negative impacts under the RCP 8.5 scenario – the most pessimistic scenario – and among farmers in the lowest productivity quantile. Table 2 presents the projected productivity impacts for the 0.25 quantile by federal unit.

**Table 2 - Projected impacts of climate change on land productivity in the lower quantile per hectare (cumulative change, 2021-2050) (0.25 Quartile)**

Federal Unit	RCP 4.5			RCP 8.5		
	Average change	Standard deviation	Confidence Interval (95%)	Average change	Standard deviation	Confidence Interval (95%)
Rondônia	18,0%	0,156	13,7% 22,2%	13,0%	0,144	9,1% 16,9%
Acre	0,4%	0,058	-2,2% 3,1%	-7,6%	0,066	-10,6% -4,5%
Amazonas	-2,1%	0,264	-9,8% 5,6%	-9,6%	0,234	-16,5% -2,8%
Roraima	-35,3%	0,107	-41,2% -29,5%	-29,0%	0,101	-34,5% -23,5%
Pará	-52,9%	0,282	-57,9% -48,0%	-64,6%	0,225	-68,5% -60,6%
Amapá	-79,6%	0,070	-83,6% -75,7%	-80,5%	0,067	-84,3% -76,7%
Tocantins	-57,7%	0,079	-59,3% -56,0%	-65,4%	0,070	-66,9% -63,9%
Maranhão	-26,3%	0,499	-33,8% -18,8%	-39,1%	0,708	-49,6% -28,5%
Piauí	-28,2%	0,322	-33,0% -23,5%	-28,2%	0,379	-33,8% -22,6%
Ceará	1,7%	0,250	-2,3% 5,6%	9,1%	0,600	-0,3% 18,5%
Rio Grande do Norte	-2,4%	0,101	-4,2% -0,7%	-5,6%	0,115	-7,5% -3,6%
Paraíba	-4,8%	0,091	-6,2% -3,4%	-7,6%	0,106	-9,2% -6,0%
Pernambuco	-10,8%	0,156	-13,3% -8,4%	-9,3%	0,160	-11,8% -6,7%
Alagoas	-14,0%	0,127	-17,1% -10,9%	-17,3%	0,103	-19,8% -14,7%
Sergipe	-24,0%	0,145	-27,7% -20,3%	-26,8%	0,134	-30,2% -23,4%
Bahia	-39,7%	0,158	-41,3% -38,1%	-41,6%	0,163	-43,2% -39,9%
Minas Gerais	-35,9%	0,200	-37,3% -34,4%	-46,8%	0,164	-48,0% -45,7%
Espírito Santo	-37,7%	0,208	-42,4% -33,0%	-49,5%	0,136	-52,6% -46,4%

Rio de Janeiro	-31,4%	0,225	-36,4%	-26,3%	-43,0%	0,161	-46,7%	-39,4%
São Paulo	-21,3%	0,092	-22,1%	-20,5%	-33,1%	0,108	-34,1%	-32,2%
Paraná	3,3%	0,244	0,7%	5,9%	1,7%	0,271	-1,1%	4,6%
Santa Catarina	-2,7%	0,201	-5,1%	-0,4%	3,6%	0,224	1,0%	6,2%
Rio Grande do Sul	11,4%	0,286	8,9%	14,0%	26,6%	0,415	22,9%	30,3%
Mato Grosso do Sul	11,8%	0,133	8,7%	14,9%	6,8%	0,153	3,3%	10,4%
Mato Grosso	-0,9%	0,149	-3,5%	1,7%	-8,9%	0,150	-11,5%	-6,3%
Goiás	-36,6%	0,081	-37,8%	-35,5%	-50,3%	0,059	-51,1%	-49,5%

Source: Prepared by the authors

The results for the lower productivity quantile (0.25) results indicate that most federal units would experience negative impacts from climate change. In the North region, the states of Amapá, Pará, Tocantins, and Roraima; in the Northeast, Bahia, Maranhão, Sergipe, Piauí, Alagoas, and Pernambuco; all federal units in the Southeast region; and the state of Goiás in the Midwest would face significant reductions in average productivity levels. Under the pessimistic scenario (RCP 8.5), the cumulative reduction could reach up to 80% in Amapá by 2050. Federal units that significantly contribute to national food production, such as Tocantins, Bahia, Minas Gerais, São Paulo, and Goiás, are also projected to experience reductions exceeding 30% in land productivity. Productivity gains are expected only in Rondônia and Acre (North), Ceará (Northeast), Paraná and Rio Grande do Sul (South), and Mato Grosso do Sul (Midwest).

The projected impacts for the median quantile (0.50) suggest that the direction of the effect remains largely unchanged across most federal units, but its intensity varies. In general, the impacts are less severe but remain negative for most federal units, with greater variation magnitude under the pessimistic scenario (RCP 8.5). Some states experience shifts in productivity trends: Rondônia, Acre, São Paulo, and Mato Grosso transition to productivity gains, while Rio Grande do Sul moves toward a decline in productivity. Mato Grosso do Sul stands out with a cumulative average productivity increase of 73% under the RCP 4.5 scenario and 89% under the RCP 8.5 scenario. Table 3 presents the projected impacts of climate change on average agricultural productivity for the 0.50 quantile.

**Table 3 - Projected impacts of climate change on median land productivity per hectare (cumulative change, 2021-2050) (0.50 Quantile)**

Federal Unit	RCP 4.5			RCP 8.5		
	Average change	Standard deviation	Confidence Interval (95%)	Average change	Standard deviation	Confidence Interval (95%)
Rondônia	40,7%	0,196	35,4% 46,0%	43,9%	0,209	38,3% 49,6%
Acre	7,6%	0,118	2,1% 13,0%	0,4%	0,119	-5,1% 5,9%
Amazonas	7,0%	0,268	-0,9% 14,8%	1,7%	0,255	-5,8% 9,1%
Roraima	-14,1%	0,127	-21,0% -7,2%	2,4%	0,127	-4,5% 9,3%
Pará	-50,5%	0,303	-55,8% -45,2%	-58,5%	0,254	-63,0% -54,1%
Amapá	-76,4%	0,080	-80,9% -71,9%	-74,0%	0,091	-79,1% -68,9%
Tocantins	-47,0%	0,103	-49,1% -44,8%	-52,1%	0,119	-54,6% -49,6%
Maranhão	-26,3%	0,364	-31,8% -20,9%	-35,4%	0,562	-43,8% -27,0%
Piauí	-23,5%	0,237	-27,0% -19,9%	-24,0%	0,258	-27,8% -20,2%
Ceará	0,0%	0,164	-2,6% 2,6%	-0,1%	0,414	-6,6% 6,4%
Rio Grande do Norte	-8,5%	0,106	-10,3% -6,7%	-17,7%	0,121	-19,8% -15,7%

Paraíba	-6,7%	0,133	-8,7%	-4,7%	-12,7%	0,142	-14,9%	-10,6%
Pernambuco	-11,8%	0,154	-14,3%	-9,4%	-12,0%	0,164	-14,5%	-9,4%
Alagoas	-21,6%	0,123	-24,6%	-18,6%	-26,6%	0,070	-28,3%	-24,8%
Sergipe	-33,3%	0,132	-36,7%	-30,0%	-37,4%	0,097	-39,8%	-34,9%
Bahia	-43,5%	0,140	-44,9%	-42,0%	-45,1%	0,140	-46,5%	-43,7%
Minas Gerais	-21,7%	0,357	-24,3%	-19,2%	-33,6%	0,303	-35,8%	-31,4%
Espírito Santo	-35,8%	0,228	-40,9%	-30,6%	-49,0%	0,161	-52,6%	-45,4%
Rio de Janeiro	-23,9%	0,253	-29,6%	-18,2%	-37,2%	0,185	-41,3%	-33,0%
São Paulo	5,6%	0,175	4,1%	7,2%	1,3%	0,210	-0,5%	3,2%
Paraná	21,1%	0,468	16,2%	26,1%	33,6%	0,582	27,5%	39,7%
Santa Catarina	-15,7%	0,219	-18,3%	-13,2%	-7,1%	0,276	-10,3%	-3,9%
Rio Grande do Sul	-2,2%	0,350	-5,3%	1,0%	18,7%	0,504	14,2%	23,2%
Mato Grosso do Sul	73,7%	0,256	67,7%	79,6%	89,2%	0,325	81,7%	96,8%
Mato Grosso	21,6%	0,159	18,8%	24,4%	20,5%	0,179	17,4%	23,6%
Goiás	-15,4%	0,123	-17,1%	-13,7%	-27,5%	0,108	-29,1%	-26,0%

Source: Prepared by the authors

Projections for the upper productivity quantile (0.75) indicate a reduction in negative impacts and an increase in positive impacts across federal units of the North, Southeast, and Midwest regions, particularly under the RCP 8.5 scenario. The states of Amazonas, Roraima, and Goiás are projected to experience productivity gains. However, Pará, Amapá, Tocantins, Minas Gerais, Espírito Santo, Rio de Janeiro, Santa Catarina, and Rio Grande do Sul, as well as all federal units in the Northeast region, are expected to see reductions in average agricultural productivity. Despite these declines, the negative effects are of lesser magnitude compared to those observed among producers in the lower productivity quantiles. Table 4 presents the projected impacts of climate change on the productivity of the upper quantile (0.75).

**Table 4 - Projected impacts of climate change on land productivity in the top quartile per hectare (cumulative change, 2021-2050) (0.75 Quartile)**

Federal Unit	RCP 4.5			RCP 8.5		
	Average change	Standard deviation	Confidence Interval (95%)	Average change	Standard deviation	Confidence Interval (95%)
Rondônia	49,4%	0,253	42,5% 56,3%	67,9%	0,351	58,4% 77,5%
Acre	4,6%	0,139	-1,8% 11,1%	1,8%	0,139	-4,6% 8,2%
Amazonas	3,3%	0,311	-5,8% 12,3%	2,0%	0,323	-7,5% 11,4%
Roraima	22,4%	0,139	14,9% 30,0%	57,0%	0,282	41,6% 72,3%
Pará	-52,7%	0,276	-57,6% -47,9%	-53,5%	0,264	-58,2% -48,9%
Amapá	-73,7%	0,082	-78,3% -69,0%	-66,6%	0,111	-72,8% -60,3%
Tocantins	-34,9%	0,154	-38,2% -31,7%	-28,9%	0,227	-33,7% -24,1%
Maranhão	-32,6%	0,269	-36,6% -28,6%	-30,5%	0,544	-38,6% -22,4%
Piauí	-18,3%	0,170	-20,8% -15,8%	-10,2%	0,210	-13,3% -7,1%
Ceará	-6,8%	0,174	-9,5% -4,0%	-2,4%	0,442	-9,3% 4,5%
Rio Grande do Norte	-17,5%	0,122	-19,6% -15,4%	-26,8%	0,141	-29,2% -24,4%
Paraíba	-10,0%	0,136	-12,0% -7,9%	-14,8%	0,162	-17,2% -12,3%
Pernambuco	-12,6%	0,128	-14,6% -10,6%	-10,7%	0,153	-13,1% -8,3%
Alagoas	-23,5%	0,171	-27,7% -19,3%	-28,4%	0,088	-30,5% -26,3%

Sergipe	-36,6%	0,132	-40,0%	-33,2%	-40,6%	0,073	-42,4%	-38,7%
Bahia	-41,9%	0,145	-43,4%	-40,4%	-41,2%	0,143	-42,7%	-39,8%
Minas Gerais	-14,4%	0,474	-17,8%	-11,0%	-19,6%	0,473	-23,0%	-16,2%
Espírito Santo	-37,6%	0,239	-43,0%	-32,2%	-47,1%	0,180	-51,1%	-43,0%
Rio de Janeiro	-26,2%	0,250	-31,8%	-20,6%	-34,7%	0,203	-39,3%	-30,2%
São Paulo	31,8%	0,392	28,3%	35,3%	51,9%	0,568	46,8%	56,9%
Paraná	46,1%	0,867	37,0%	55,2%	91,0%	1,304	77,2%	104,7%
Santa Catarina	-24,1%	0,286	-27,4%	-20,8%	-12,6%	0,425	-17,5%	-7,7%
Rio Grande do Sul	-6,2%	0,453	-10,2%	-2,1%	23,8%	0,730	17,3%	30,4%
Mato Grosso do Sul	172,3%	0,568	159,1%	185,5%	255,1%	0,854	235,2%	275,0%
Mato Grosso	31,6%	0,210	28,0%	35,3%	48,8%	0,296	43,7%	54,0%
Goias	3,4%	0,191	0,7%	6,2%	5,3%	0,217	2,2%	8,4%

Source: Prepared by the authors

The projections indicate a concentration of negative effects on federal units within the North, Northeast, and Southeast regions. However, positive impacts are observed in São Paulo, Acre, Amazonas, and Ceará. The Midwest and South regions experience milder effects, with productivity gains in Rio Grande do Sul, Paraná, Mato Grosso, and Mato Grosso do Sul. With some caveats, this spatial pattern of impacts aligns with findings from other studies, such as Tanure *et al.*, (2024), Feres *et al.*, (2009), and Pinto *et al.*, (2008). This pattern and is primarily associated with higher temperature increases and reduced precipitation in these regions.

From a comparative perspective across productivity quantiles, the projections indicate that the most severe negative impacts are concentrated among the least productive farmers in the 0.25 quantile. In contrast, positive impacts are primarily observed among the most productive farmers in the 0.75 quantile. This pattern is evident in Maranhão, Piauí, Paraná, and in the North, Southeast, and Midwest region.

However, the Northeast region, along with the states of Santa Catarina and Rio Grande do Sul, exhibits a distinct pattern, where higher-productivity farmers experience greater negative impacts. This trend is particularly noticeable in the Northeast states of Ceará, Rio Grande do Norte, Paraíba, Pernambuco, Alagoas, and Sergipe. The impact pattern across productivity quantiles is best visualized from an aggregated regional perspective, which is presented in the following section.

The impacts of climate change across land productivity quantiles suggest that farmers with less control over the production process would be more adversely affected. This finding aligns with the results of Tanure *et al.*, (2024), who analyzed the difference in climate impacts between family farmers and large-scale farmers, demonstrating that large-scale farmers, particularly those with higher productivity levels, are less vulnerable by climate phenomena. Additionally, the projections support the findings of DePaula (2020), which also indicate that less productive farmers in the North region experience greater negative impacts.

### 3.2 Results by aggregate regions

This section presents the projections of climate change impacts on family farming land productivity at the regional and for Brazil as a whole. Similar to the projections for federal units, the results for macro-regions and Brazil are based on productivity averages weighted by the production areas of each municipality. Thus, the aggregated results are not a simple average of the federal unit results,

but rather an aggregation of municipal-level outcomes within each region, ensuring that larger production areas have a greater influence on the overall productivity impact. Table 5 presents the aggregated results.

**Table 5 - Projected impacts of climate change on land productivity per hectare (cumulative variation, 2021-2050)**

Productivity Quantile	Region	RCP 4.5			RCP 8.5		
		Average change	Standard deviation	Confidence Interval (95%)	Average change	Standard deviation	Confidence Interval (95%)
0.25	North	-37,4%	0,37	-41,2% -33,5%	-46,6%	0,36	-50,4% -42,9%
	Northeast	-19,3%	0,29	-20,8% -17,9%	-19,6%	0,43	-21,9% -17,4%
	Southeast	-32,3%	0,19	-33,3% -31,3%	-43,6%	0,16	-44,5% -42,8%
	South	6,3%	0,26	4,7% 7,8%	13,8%	0,36	11,7% 16,0%
	Midwest	-8,1%	0,23	-10,4% -5,8%	-16,9%	0,26	-19,4% -14,3%
	Brazil	-9,4%	0,31	-10,3% -8,5%	-8,8%	0,42	-10,0% -7,6%
0.50	North	-30,4%	0,43	-34,9% -25,9%	-35,6%	0,44	-40,2% -31,0%
	Northeast	-21,6%	0,25	-22,9% -20,4%	-24,1%	0,33	-25,8% -22,4%
	Southeast	-17,0%	0,33	-18,7% -15,2%	-27,1%	0,31	-28,8% -25,5%
	South	4,6%	0,41	2,2% 7,0%	20,5%	0,53	17,4% 23,6%
	Midwest	23,6%	0,38	19,9% 27,3%	23,6%	0,48	18,8% 28,3%
	Brazil	-5,6%	0,39	-6,7% -4,5%	-0,5%	0,51	-1,9% 1,0%
0.75	North	-29,2%	0,45	-33,9% -24,4%	-26,0%	0,52	-31,4% -20,5%
	Northeast	-23,6%	0,22	-24,8% -22,5%	-22,5%	0,33	-24,1% -20,8%
	Southeast	-6,4%	0,48	-9,0% -3,9%	-5,8%	0,58	-8,9% -2,7%
	South	10,8%	0,69	6,8% 14,9%	43,7%	1,03	37,6% 49,7%
	Midwest	57,8%	0,75	50,4% 65,2%	86,8%	1,10	75,9% 97,7%
	Brazil	1,1%	0,61	-0,6% 2,9%	19,5%	0,90	16,9% 22,1%

Source: Prepared by the authors

The projected results for the lower productivity quantile (0.25) indicate that climate change would negatively impact the North, Northeast, Southeast, and Midwest regions. The North and Southeast regions are expected to experience the most severe impacts, with average productivity reductions of 37% and 32% under the RCP 4.5 scenario. Only the South region is projected to benefit from increased productivity. Under the RCP 8.5 scenario, the magnitude of the impacts would be amplified, albeit with variations across regions. The aggregated results for Brazil suggest an average productivity reduction of 9.4% under the RCP 4.5 scenario and 8.5% under the RCP 8.5 scenario.

For the median productivity quantile (0.50), compared to the lower quantile (0.25), the results indicate continued negative impacts in the North, Northeast, and Southeast regions, as well as positive impacts in the South. The Midwest region transitions to productivity gains of approximately 23% under both scenarios. Although the North and Southeast continue to experience negative impacts, these effects are less severe. Conversely, the negative impacts intensify in the Northeast, with productivity reductions of 21.6% under the RCP 4.5 scenario and 24% under the RCP 8.5 scenario. For Brazil as a whole, the median productivity quantile projects an average decline of 5.6% under the RCP 4.5 scenario and 0.5% under the RCP 8.5 scenario.

When comparing the results for the median productivity quantile (0.50) – which represents the median productivity of family farmers – with the findings of Assunção and Chein (2016), who analyzed aggregated agricultural production using a different methodology, the direction and magnitude of effects appear similar for the North, Northeast, and Southeast regions. Assunção and Chein (2016) estimate productivity reductions of 35% in the North, 27% in the Northeast, and 16.8% in the Southeast, as well as declines of 28% in the Midwest and 4% in the South. These effects correspond to an 18% reduction in national production by 2050.

For the upper productivity quantile (0.75), projections indicate negative impacts on aggregate productivity in the North, Northeast, and Southeast regions, while positive impacts are observed in the South and Midwest regions. Under the RCP 8.5 scenario, the direction of impacts remains consistent; however, the magnitude of negative effects diminishes, while positive effects on productivity intensify. The Midwest region stands out, with projected cumulative productivity increases of 57% by 2050 under the RCP 4.5 scenario and 86% under the RCP 8.5 scenario. At the national level, aggregated average productivity is projected to increase by 1% under the RCP 4.5 scenario and 19% under the RCP 8.5 scenario, primarily driven by productivity gains in the South and Midwest regions.

A clear pattern of impacts emerges across family farming productivity profiles, with more severe negative effects on lower-productivity farmers and milder or positive effects on higher-productivity farmers. This trend is evident in Brazil's aggregated average productivity results, where under the RCP 4.5 scenario, lower-productivity farmers experience a 0.4% decline, intermediate-productivity farmers face a 5%, and higher-productivity farmers see a 1% increase. The distinction is even more pronounced under the RCP 8.5 scenario, with average productivity declines of 8.8% for lower-productivity farmers, while higher-productivity farmers achieve productivity gains of 19.5%.

The greater sensitivity of less productive family farming to the effects of climate change may lead to an increased state of vulnerability for this segment of producers. Adger (2006) defines vulnerability as an adverse outcome resulting from a system's susceptibility and inability to cope with the effects of climate change at the time it occurs. However, despite being more adversely affected, land productivity in this segment can be enhanced through the adoption of mechanization, technology, fertilization, irrigation, and other factors that contribute to productivity gains and, consequently, help mitigate the adverse effects of climate change. Therefore, although less productive farmers face greater impacts, they also have more opportunities for compensatory adaptation measures, surpassing the potential for adaptation observed among more mechanized and productive farmers. The inherent flexibility and diversity of family farming are key attributes that support the adaptation of these producers to climate change (Chao, 2024).

Despite the greater potential for adaptation among less productive family farmers, it is crucial to emphasize that this group faces significant challenges in accessing credit and technical assistance. Data from the Agricultural Census (IBGE, 2019) highlight this gap, showing that, at the national level, only 15% of family farmers accessed financing for operational or investment purposes in 2017, and only 18% reported receiving technical assistance.

The vulnerabilities of family farming exhibit distinct spatial patterns. As demonstrated, the North, Northeast, and Midwest regions are projected to be the most adversely affected by declines in land productivity. Among these, the North and Northeast have a higher concentration of subsistence-

oriented farmers. According to the Agricultural Census (IBGE, 2019), only 8.8% of family farmers in the North and 7.3% in the Northeast have access to technical assistance. This situation contrasts sharply with the South and Southeast regions, where 48.8% and 24.5% of family farmers, respectively, have access to technical assistance – the highest participations levels in the country.

As noted by Garcia and Buainaim (2024), a large portion of family farmers, even when eligible for public agricultural support programs such as Pronaf<sup>2</sup> and the ABC+ Plan<sup>3</sup>, often do not receive technical or financial assistance, leaving them on the fringes of these initiatives. Moreover, the lack of specific support policies for family farmers represents an institutional weakness, highlighting yet another dimension of the vulnerability these producers face.

According to Adger (2000), institutional frameworks play a central role in linking social and ecological resilience, as opportunities and prospects are closely tied to the diversity of existing institutions and their operational efficiency. Eiró (2010) emphasizes that building adaptive capacity through the improvement of socioeconomic conditions and the strengthening of formal and informal institutions is a key strategy in reducing local vulnerabilities. In this context, a redesign of public policies, such as the ABC+ Plan, that the productive and regional specificities of family farmers is imperative to reduce their vulnerability, as argued by Garcia and Buainaim (2024).

Therefore, it is crucial to thoroughly understand and assess social and economic processes, with vulnerability broadly defined as "the starting point" for analyzing impacts. In the case of family farmers, social and institutional fragility has strong regional component and is further exacerbated by the greater economic impact of adverse effects on land productivity. In this sense, adaptive measures are essential to mitigate these impacts, emphasizing the actions and conditioning factors that influence adjustments at the community and family levels (Kelly and Adger, 2000; Kirsch and Schneider, 2016).

#### **4. Final Considerations**

This study aimed to assess the impacts of climate change on family farming land productivity in Brazil, focusing on two key aspects: (i) the productive structure of family farmers, given the significant heterogeneity in farmer profiles across the country, and (ii) the spatial variability of climatic effects, which also differs across Brazil's regions. The results indicate that climate change would impact land productivity differently across various profiles of family farmers.

Less productive family farmers, who are notably more vulnerable, would experience greater negative impacts than their more productive counterparts. This pattern is evident when comparing the impacts among the bottom 25% of producers in terms of productivity, those with median productivity, and the top 25% of most productive farmers. The findings suggests that climate change could exacerbate the vulnerability of less productive farmers. However, this vulnerability can be mitigated through the adoption of productive factors that enhance land productivity. In this regard, low-productivity family

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<sup>2</sup> The National Program for Strengthening Family Farming (PRONAF) aims to promote sustainable development in rural areas through actions aimed at increasing production capacity, generating jobs, and raising income through lines of credit appropriate to the needs of family farmers (Brasil, 2001).

<sup>3</sup> The Adaptation and Low Carbon Emissions Plan in Agriculture, is a national strategic agenda of the Brazilian government that continues the sectoral policy to tackle climate change in the agricultural sector, its main goal is to promote adaptation to climate change and control of GHG emissions in Brazilian agriculture, increasing the efficiency and resilience of production systems, considering an integrated landscape management. (Brasil, 2024).

farmers have greater potential for adaptation, as they possess more flexibility for in the production process compared to more productive farmers.

The effects of climate change are heterogeneous, and while productivity impacts vary within a single region, negative effects are primarily concentrated in the North, Northeast, and Southeast regions. Conversely, the South and Midwest regions are projected to benefit from productivity gains. Federal units with significant contributions to food production, such as São Paulo, Mato Grosso do Sul, Paraná, and Rio Grande do Sul, are expected to experience average productivity increases, which could help reduce the negative effects in other states. However, regions dominated by subsistence-oriented family farming are projected to face declines in average productivity. Thus, climate change could not only increase the vulnerability of the most fragile producers but also exacerbate regional disparities.

## References

- Adger, W. N. (2000). Social and ecological resilience: Are they related? *Progress in Human Geography*, 24(3), 347-364.
- Adger, W. N. (2006). Vulnerability. *Global Environmental Change*, 16(3), 268-281.
- Assad, E. D., & Pinto, H. S. (2008). *Global warming and future scenarios of Brazilian agriculture*. São Paulo: Embrapa/Unicamp.
- Assunção, J., & Chein, F. (2016). Climate change and agricultural productivity in Brazil: Future perspectives. *Environment and Development Economics*, 21(5), 581-602.
- Barbosa, E., Feres, J., Haddad, E., & Paez, A. (2020). Climate change and land use patterns in Brazil. *Innovations in Urban and Regional Systems: Contributions from GIS&T, Spatial Analysis and Location Modeling*, 443-472.
- Brasil. (2001). Presidência da República. Casa Civil. Subchefia para Assuntos Jurídicos. Decreto Nº 3.991, de 30 de outubro de 2001. O Programa Nacional de Fortalecimento da Agricultura Familiar – PRONAF. Retrieved from [https://www.planalto.gov.br/ccivil\\_03/decreto/2001/D3991.htm](https://www.planalto.gov.br/ccivil_03/decreto/2001/D3991.htm).
- Brasil. (2023). Ministério da Agricultura e Pecuária. Programas e Estratégias. Plano ABC+. Retrieved from <https://www.gov.br/agricultura/pt-br/assuntos/sustentabilidade/planoabc-abcmais/abc/programas-e-estrategias>.
- Brazilian Institute of Geography and Statistics – IBGE. (2017). *Agricultural Census 2017*. Rio de Janeiro: IBGE.
- Buchinsky, M. (1998). Recent advances in quantile regression models: A practical guideline for empirical research. *Journal of Human Resources*, 33(1), 88-126.
- Chao, K. (2024). Family farming in climate change: Strategies for resilient and sustainable food systems. *Heliyon*, 10(7), e28599. <https://doi.org/10.1016/j.heliyon.2024.e28599>.

- Chou, S. C., Lyra, A., Mourão, C., Dereczynski, C., Pilotto, I., Gomes, J., Bustamante, J., et al. (2014). Assessment of climate change over South America under RCP 4.5 and 8.5 downscaling scenarios. *American Journal of Climate Change*, 3(5), 512.
- DePaula, G. (2020). The distributional effect of climate change on agriculture: Evidence from a Ricardian quantile analysis of Brazilian census data. *Journal of Environmental Economics and Management*, 104, 102378.
- Eiró, F. (2010). Vulnerabilidade socioeconômica da agricultura familiar brasileira às mudanças climáticas: O desafio da avaliação de realidades complexas. *Boletim Regional, Urbano e Ambiental*, 4, 21-31.
- Escher, F., Schneider, S., Scarton, L. M., & Conterato, M. A. (2014). Characterization of pluriactivity and multi-income in Brazilian agriculture based on the 2006 Agricultural Census. *Journal of Rural Economics and Sociology*, 52, 643-668.
- FAO. (2003). Impact of climate change on food security and implications for sustainable food production. *Committee on World Food Security, 29th Session, Rome*.
- FAO. (2014). What do we really know about the number and distribution of farms and family farms in the world? *Background paper for The State of Food and Agriculture*.
- Féres, J. G., Reis, E. J., & Speranza, J. S. (2011). Impact of climate change on the Brazilian agricultural sector. In R. Seroa da Motta, J. Hargrave, G. Luedemann, & M. B. S. Gutierrez (Eds.), *Climate change in Brazil: Economic, social and regulatory aspects* (pp. 299-309). Brasília: IPEA.
- Garcia, J. R., & Buainain, A. M. (2024). Mudanças climáticas e a necessidade de uma agricultura familiar de baixo carbono no Brasil. *Boletim Regional, Urbano e Ambiental*, 33. DOI: <https://dx.doi.org/10.38116/brua33>.
- Helfand, S. M., & Taylor, M. P. (2021). The inverse relationship between farm size and productivity: Refocusing the debate. *Food Policy*, 99, 101977. <http://dx.doi.org/10.1016/j.foodpol.2020.101977>.
- Koenker, R., & Bassett, G. (1978). Regression quantiles. *Econometrica*, 46(1), 33-50.
- Matsuura, K., & Willmott, C. J. (2012). Terrestrial air temperature: 1900–2010 gridded monthly time series. Retrieved from [http://climate.geog.udel.edu/~climate/html\\_pages/Global2011/GlobalTsT2011.html](http://climate.geog.udel.edu/~climate/html_pages/Global2011/GlobalTsT2011.html).
- Tanure, T. M. P., Domingues, E. P., & Magalhães, A. S. (2024). Regional impacts of climate change on agricultural productivity: Evidence on large-scale and family farming in Brazil. *Journal of Rural Economics and Sociology*, 62(1), e262515. <https://doi.org/10.1590/1806-9479.2022.262515>.