

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

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Abstract

Purpose – Family farming (FF) 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 change. In this context, this study analyzes the impacts of climate change on different quantiles of land productivity in FF across Brazil's federal units and macro-regions.

Design/methodology/approach – The methodology encompasses a microfounded theoretical model that guides the cross-sectional estimation of a quantile regression of land productivity, considering climatic, geographic and productive factors.

Findings – 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.

Research limitations/implications – 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.

Practical implications – The results point to negatively affected regions, which can be used by policymakers in the context of climate change adaptation policies.

Originality/value – The work is an original contribution to the literature on the impacts of climate change on FF 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

Paper type Research article

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 National Institute for Space Research (INPE) (Chou *et al.*, 2014) 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

JEL Classification — Q1, Q13, Q54

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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, Domingues, & Magalhães, 2024; Assad & Assad, 2024; De Paula, 2020).

Family farming (FF) plays an important role in the current production system from social, economic and environmental perspectives. According to the Agricultural Census (IBGE, 2019), FF 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), 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, FF is distinctly structured compared to large-scale agriculture. 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, Schneider, Scarton, & Conterato, 2014).

This last aspect is regionally evident in Brazil. Producers in the South, Southeast and Midwest regions demonstrate stronger market integration, higher participation in the National Program for Strengthening Family Farming (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 CO₂ 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).

For Brazil, projections by Assad *et al.* (2016) indicate a reduction in agricultural suitability for crops such as rice, coffee, beans, sunflower, corn and soybeans. Regionally, Fêres, Reis, and Speranza (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.

Recent CMIP6-based assessments also indicate that climate change is expected to reduce the productivity of all major crops in Brazil, with the most severe losses concentrated in the Amazon, Cerrado and Caatinga biomes. Staple crops such as maize, beans, rice and second-crop maize, central to FF, are projected to experience substantial yield declines due to rising temperatures, increased water deficits and a higher frequency of extreme heat and rainfall events (Marengo, 2025).

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 FF productivity remain scarce. [Tanure et al. \(2024\)](#) estimate higher sensitivity of FF 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 FF in Brazil.

Therefore, considering that the productive structure shapes the sensitivity of productivity to climate change and that significant productive heterogeneity exists even within FF, 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 FF 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 literature review. [Section 3](#) presents the materials and methods, describing the theoretical model that informs the quantile regression estimation and presenting the dataset used. [Section 4](#) reports the estimation results by federal units. [Section 5](#) provides a discussion of the findings. The concluding section summarizes the study's main contributions.

2. Literature review

The assessment of climate change impacts on agriculture involves substantial conceptual and empirical complexity, as it spans biophysical, economic and social dimensions, unfolds over long horizons and introduces uncertainty and externalities. In the empirical literature, three main methodological approaches have been used to estimate climate–agriculture relationships: the production function (agronomic) approach, the Ricardian (hedonic) approach and the Agroecological Zone (AEZ) modeling framework. Each provides a distinct perspective on how climate variables affect agricultural productivity and land use, differing mainly in how they incorporate adaptation and behavioral responses.

The production function approach specifies a crop-specific production function to isolate the direct effect of climatic variables, such as temperature, precipitation and CO₂ concentration, on yields. This method, commonly applied in agronomic studies, estimates “pure” climatic effects by keeping other inputs constant ([Féres, Reis, & Speranza, 2009](#); [Assunção & Chein, 2016](#)). Many studies rely on controlled experiments or process-based crop models that simulate biophysical responses to alternative climatic conditions ([FAO, 2000](#)). While these models are useful for identifying physiological yield responses, they do not allow producers to adapt production techniques, and thus they tend to overestimate negative impacts. Furthermore, because of the high cost of experimentation, agronomic studies typically focus on major staple crops ([Mendelsohn, Basist, Kurukulasuriya, & Dinar, 2007](#)).

The Ricardian or hedonic approach, introduced by [Mendelsohn, Nordhaus, and Shaw \(1994\)](#), represents an alternative framework in which land value serves as the dependent variable, reflecting the discounted stream of expected future agricultural profits. Under the assumption of efficient land markets, land prices internalize long-run adaptation to local

climate, technology and institutional conditions. This method captures spatial equilibrium relationships between climate and profitability, thus implicitly incorporating adaptation. However, Ricardian models also have limitations: they are static and cross-sectional, omit transaction costs and irrigation, and typically assume fixed output prices (Kurukulasuriya *et al.*, 2006; Seo & Mendelsohn, 2008). In developing countries, land prices may be influenced by speculative or nonproductive motives, such as collateral, hedging against inflation or asset storage, which weakens their interpretation as purely agricultural returns (Assunção & Chein, 2016).

To address these issues, extended Ricardian models were developed. Seo and Mendelsohn (2008) proposed the Generalized Mendelsohn Adaptive Production model, which introduces an endogenous behavioral component by allowing farmers to reallocate resources among alternative land uses in response to climatic shifts. This improvement enables a more realistic depiction of adaptive responses to long-term changes in temperature and precipitation.

The third main strand of research employs the AEZ framework, developed by FAO (1996, 2000). AEZ models simulate potential agricultural productivity by integrating data on soil, topography and climate with eco-physiological parameters of crops, such as photosynthetic potential, growth cycles and harvest indices. These models can incorporate different technological levels and estimate the suitability of each crop for given environmental conditions. AEZ simulations have been applied in Brazil since the mid-1990s, initially through the Ministry of Agriculture's Agroclimatic Risk Zoning (ZARC) program, which combines AEZ outputs with IPCC climate scenarios to define crop calendars and risk maps (Assad & Pinto, 2008; Assad *et al.*, 2016). The main advantage of AEZ is its strong integration with biophysical processes, though it remains data-intensive and less suitable for economic inference.

Using an agronomic model, Assad *et al.* (2016) made a detailed review of the effects of temperature on soybean, bean, corn, coffee, sugarcane, orange and cocoa crops, indicating how the increase in temperature can affect the development and productivity of these crops. Recent evidence from the National Institutes of Science and Technology (INCT) Report (Marengo, 2025) provides an updated and policy-relevant assessment of climate impacts on Brazilian agriculture under CMIP6-based scenarios. Using agrometeorological models calibrated with CMIP6 projections, the report concludes that, in the absence of adaptation, no major crop presents productivity gains in any biome. Losses are particularly severe in the Amazon, followed by the Cerrado and Caatinga, with smaller yet negative impacts in the Atlantic Forest and Pampa. Staple crops that are central to FF, such as maize, second-crop maize, beans and rice, show high vulnerability to heat stress, water deficits, and increases in the frequency of days above 34°C and extreme rainfall events. These findings reinforce the consensus across the Brazilian literature that climate change disproportionately affects low-latitude regions and FF systems, while also highlighting the potential of adaptive practices such as integrated crop–livestock–forestry systems (ILPF), which the report identifies as a major opportunity for restoring degraded pastures and partially offsetting climate-induced productivity losses.

Regarding empirical evidence for Brazil, most economic studies assessing climate change impacts on Brazilian agriculture rely on the Ricardian or hybrid approaches, sometimes complemented by AEZ-based simulations. The seminal work by Sanghi, Alves, Evenson, and Mendelsohn (1997) used both a hedonic model and a crop-level production function to evaluate temperature and precipitation effects on land use and productivity, concluding that the Midwest region would suffer major productivity losses while the South could experience gains. Evenson and Alves (1998) extended this framework by incorporating public and private R&D variables, showing that technological innovation offsets part of the climatic damage, mainly by expanding cultivated land at the expense of natural pasture.

Building on these studies, Féres *et al.* (2009) estimated a simultaneous system of land-use equations consistent with microeconomic profit maximization, using IPCC's A2 and B2 climate scenarios. Their results reveal regional heterogeneity: deforestation pressure and agricultural expansion in the North, moderate declines in the Northeast and gains in the South linked to higher average productivity. Average agricultural productivity declines were found

for the North, Northeast and Center-West, especially for subsistence crops such as maize, beans and rice.

Using a more spatially disaggregated dataset, [Massetti, Nascimento Guiducci, Fortes de Oliveira, and Mendelsohn \(2013\)](#) estimated a regional Ricardian model across multiple IPCC climate scenarios (A2), combining cross-sectional census data from 1975 to 2006. They found overall negative impacts nationwide, with the most severe losses in the North and Northeast and modest gains in the South. A 1°C temperature increase was estimated to reduce average land value, though effects varied across climate models, underscoring the importance of scenario uncertainty.

In a more recent contribution, [De Paula \(2018\)](#) employed a quantile Ricardian framework using the 2006 Agricultural Census. The study uncovered strong heterogeneity: a 1°C temperature increase reduces land values by 5% for high-productivity farmers in the South and by 34% for low-productivity farmers in the North, effectively doubling productivity inequality across the distribution. This work provided the first empirical evidence of how climate change may exacerbate regional and social disparities in Brazilian agriculture.

Brazilian studies also have adopted intermediate or hybrid frameworks that link the Ricardian valuation logic with production-function specifications, combining spatial climate variation with explicit productivity measures. [Assunção and Chein \(2016\)](#) developed a cross-sectional model of average agricultural productivity across municipalities, relating it to geographic and climatic attributes under the IPCC A1B scenario (2030–2049). Their estimates point to an 18% national decline in agricultural productivity per hectare, with effects ranging from –40% to +15% at the municipal level and with the largest losses concentrated in the North, Northeast and Center-West.

[Bragança \(2015\)](#) decomposed climate effects into intensive (yield) and extensive (land reallocation) margins, applying RCP 4.5 and 8.5 scenarios. The study found national productivity reductions of 21% to 30% by mid-century and up to 47% by 2100, with expansion of pasture and forestry areas in response to climatic stress. [Miyajima \(2018\)](#) adopted a similar model, coupling productivity shocks to a Computable General Equilibrium model to assess broader economic repercussions in the Legal Amazon region. Using RCP 4.5 and 8.5 scenarios for 2021–2080, results indicated an average 12% national decline in productivity, with losses above 40% in the Northeast and substantial gains in the South.

[Tanure et al. \(2024\)](#) analyzed the effects of climate change on agricultural productivity across Brazilian regions, distinguishing between family and large-scale farming. They found that FF is more climate-sensitive, as limited use of capital and technology increases vulnerability to temperature and rainfall changes. Negative impacts are concentrated in the North and Northeast, where subsistence farming prevails, while the South shows productivity gains, and the Midwest and Southeast experience moderate effects. At the crop level, cassava, coffee, maize, beans and oranges are most affected in FF, whereas sugarcane, grapes and wheat benefit in large-scale farming.

Collectively, this body of work highlights a consistent pattern of spatial heterogeneity and asymmetric vulnerability: the northern and northeastern regions tend to face significant productivity declines, while southern states may benefit from moderate warming. Methodologically, recent studies converge toward models that bridge agronomic and Ricardian traditions, retaining the microeconomic logic of land allocation while exploiting spatial climatic variation to estimate productivity responses. This paper builds directly on this hybrid literature, adopting a quantile regression approach to examine how climate change affects different productivity profiles within FF across Brazilian regions, thereby contributing a novel perspective on heterogeneous vulnerability under climate change.

3. 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 L_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 L_{mk} and inputs I_{mk} allocated to this crop, as well as a vector with climatic and geographic characteristics CG_m :

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

γ_{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 L_{mk} . The indirect profit function for this problem is defined as:

$$V_{mk}(L_{mk} | CG_m) = \max [X_{mk} \gamma_{mk} f^k(L_{mk}, I_{mk} | CG_m) - w_m I_{mk}] \quad (2)$$

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

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

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

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

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

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

$$\sum_k L_{mk}^*(CG_m) = L_m \quad (5)$$

Equations (4) and (5) illustrate how climate change in CG_m influences producers' decision-making, particularly in terms of agricultural productivity, implicitly defining the optimal land allocation. If the vector with the climatic characteristics shifts from CG_m to CG'_m , the marginal value of the different agricultural activities will be affected heterogeneously. Thus, the land allocation $L_{mk}^*(CG'_m)$ will differ from the initial allocation of land $L_{mk}^*(CG_m)$, 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 the static spatial adjustment of land allocation to climatic heterogeneity. It represents how producers, given current climatic and geographic conditions, would allocate land among crops in a comparative-static framework. Therefore, it should not be interpreted as a dynamic process of adaptation over time, but rather as a spatial reallocation pattern under different climatic regimes.

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:

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

In the theoretical model, Y_{mk} denotes an idiosyncratic productivity shifter that varies by municipality and crop. This term represents structural differences across municipalities, such as baseline technological conditions, access to inputs and infrastructure, soil management practices and local institutional environments, that are not directly determined by climate. Given the cross-sectional nature of the data, Y_{mk} is treated as an exogenous productivity component rather than the outcome of short-run farmer decisions. In the empirical specification, this heterogeneity is absorbed by the set of observable controls included in the quantile regressions (capital, labor, irrigation, soil attributes and other structural variables), as well as by the quantile-specific intercepts. Accordingly, Y_{mk} does not appear explicitly in the reduced-form equation, but it motivates the inclusion of these controls to ensure that the estimated climatic coefficients reflect productivity responses conditional on each municipality's structural characteristics.

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 Brazilian 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:

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

[Equations \(6\)](#) and [\(7\)](#) define agricultural productivity, which depends on γ_{mk} , geographic, productive and climatic factors, and serve as the foundation for the empirical analysis conducted in the next section. These equations enable the estimation of how FF productivity quartiles respond to climatic factors.

3.1 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, Feres, Haddad, and Paez \(2020\)](#) and [Tanure et al. \(2024\)](#). However, this study introduces an innovation by employing quantile regression to capture the effects of climate on different productivity quantiles of FF. Quantile regression offers a more robust alternative to the ordinary least squares (OLS) estimation, which focuses solely on the 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 & Bassett, 1978](#); [Buchinsky, 1998](#)). This feature is particularly valuable for analyses involving FF, 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. Although factor prices vary across regions, the empirical specification includes detailed productive and geographic controls, such as labor intensity, capital value, irrigation, soil correction, soil type and improvements, which partially absorb differences in wages, capital costs, land quality and infrastructure. These controls serve as a proxy for local production conditions and mitigate omitted variable bias, following the approach adopted by [Assunção and Chein \(2016\)](#), [Barbosa et al. \(2020\)](#) and [Tanure et al. \(2024\)](#). 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 ϵ_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 γ_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 τ 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. While OLS captures only average marginal effects, quantile regressions minimize the quantile check loss function and recover the marginal climatic impacts for specific points of the productivity distribution. This allows us to examine how temperature and precipitation affect low-productivity ($\tau = 0.25$), median-productivity ($\tau = 0.50$) and high-productivity ($\tau = 0.75$) FF municipalities. Because each quantile regression uses the full sample but is identified primarily by observations near the target quantile, the method is well suited to the strong structural heterogeneity observed within FF. By uncovering how climatic sensitivity varies across productivity levels, the quantile approach offers new insights that are not available in average-effect models and represents an important contribution to the empirical literature on climate impacts in Brazilian FF.

After estimating the model represented in [equation \(11\)](#), the average temperature and precipitation variables (CG_m) are replaced, in the same model, by their projected values (CG'_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.

$$\ln Y_m = \theta(CG'_m) + \beta' X_m + \epsilon_m \quad (12)$$

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

$$\Delta \ln Y_m = [\theta(CG_m) + \beta' X_m] - [\theta(CG'_m) + \beta' X_m] \quad (13)$$

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 $\Delta Y^* = Y^*_{m1} - Y^*_{m0}$.

The cross-sectional variation is used solely to estimate the climate coefficients, while the counterfactual simulations of climate change are performed within each municipality, replacing only its climatic variables and keeping all productive characteristics fixed. The resulting projections should therefore be interpreted as mechanical, non-causal simulations of how productivity would change if local climatic conditions shift, under the assumption of no adjustments in technology or input use.

In this framework, the productive structure captured in the analysis reflects the 2017 baseline data, embodying the cumulative effects of historical development paths, institutional conditions and differential access to capital and technology that shaped agricultural production at that point in time. As a result, the simulations isolate the contribution of climate, holding these underlying determinants constant. In other words, the simulations do not incorporate future changes in capital accumulation, technological adoption or institutional conditions,

which are central determinants of productivity growth. While these factors are implicitly reflected in the 2017 database, their evolution over time is not modeled. Therefore, the estimated impacts represent the isolated contribution of climate under the current structural configuration, rather than projections of overall productivity dynamics.

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; Féres *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, Hanemann, & Fisher, 2006).

It is important to emphasize that the empirical model does not identify behavioral or dynamic adaptation. In the counterfactual simulations, only the climatic variables are modified, while all productive factors remain fixed at their observed levels. Thus, the projected impacts represent the pure static effect of climate on land productivity, abstracting from technological change, learning or intertemporal adjustment. Any reference to “adaptation” in the manuscript refers only to the potential technological or productive improvements required to offset projected losses and not to adaptation estimated from the data. 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 & Chein, 2016).

3.2 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 FF 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.

All establishments included in the analysis are classified as FF units according to the official criteria of Law 11.326/2006, as operationalized in the 2017 Agricultural Census. This classification considers farm size, reliance on predominantly family labor, family-based management and the predominance of agricultural income. The selection of crops is used solely to delineate relevant production activities within the FF. All productivity and input-use variables are therefore constructed exclusively from establishments that meet the Census definition of FF.

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: (1)

Machinery Value (the natural logarithm of the value of machinery, equipment and tractors available on properties, per hectare); (2) Labor Intensity (the natural logarithm of the number of workers per hectare); (3) Improved area (the area occupied by buildings, improvements or pathways); (4) Irrigated Area (measured in hectares); (5) Soil pH Correction Participation (the percentage of establishments that applied soil pH correction); (6) Predominant Soil Type (categorical classification of soil characteristics); (7) geographic variables (altitude, latitude and longitude, at the municipal level, extracted from Ipeadata database).

To isolate the direct climatic effect on land productivity, the empirical model includes a detailed set of control variables that capture technological, productive and soil-related heterogeneity across municipalities. Labor, capital and irrigation reflect differences in technology adoption, factor availability and production costs, while soil type, pH correction and soil improvements provide proxies for land quality, an important source of endogeneity in cross-sectional climate–agriculture studies. By conditioning on these observable attributes, the model reduces omitted variable bias and ensures that the estimated coefficients on climatic variables represent static climatic associations, rather than adaptive behavior or unobserved structural differences.

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 Willmott \(2012\)](#). The temporal scope for constructing the baseline model corresponds to a climatological normal [1] period of 34 years, from 1971 to 2005.

Although the 2006 Agricultural Census is temporally closer to the 1971–2005 climatological normal, we rely on the 2017 Census because it provides a substantially more accurate representation of Brazil's current productive structure. The period between 2006 and 2017 witnessed marked changes in agricultural practices, especially within FF, such as increased mechanization, expansion of capital stock, greater access to irrigation and improvements in soil and land management. Using 2006 data would therefore introduce a highly outdated characterization of input use and technology adoption. Since the climatic variables reflect long-term averages that change only gradually over time, the modest temporal gap has limited impact on the climatic baseline, whereas the 2017 Census markedly improves the quality and relevance of the productive controls used in the empirical model. [Figure A1](#) in the [Supplementary material](#) presents historical municipal-level data for average temperature and precipitation across Brazil, providing a spatial representation of these climatic factors.

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 2,100, 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 2,100 ([IPCC, 2014](#)). [Figure A2](#), in the [Supplementary material](#), illustrates the precipitation and temperature projections for the respective climate scenarios.

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 A1](#)), 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. Although we rely on RCP4.5 and RCP8.5, differences between CMIP5 and the most recent CMIP6 remain modest through mid-century, with major divergence only after 2070. For 2021/2050, temperature and precipitation anomalies show similar direction and magnitude across SSP2 and SSP5 scenarios ([IPCC AR6, 2021](#)).

4. Results and discussion

To project the impacts of climate change on FF land productivity, while accounting for productive specificities and spatial climatic heterogeneity, this study first estimated a baseline model represented by [equation \(11\)](#). In this model, aggregate land productivity of FF 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 [\[2\]](#) indicates how productive, geographic and historical climatic factors influence FF land productivity.

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 are 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 1°C 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 with 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 exhibit greater capital intensity. 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.

The quantile regressions reveal a decline in the marginal effect of capital and property improvements as productivity increases. In the 0.25 quantile, where family farmers operate with low mechanization and limited technological inputs, the elasticity of land productivity with respect to capital is approximately 0.53 ($p < 0.01$), indicating marginal gains from additional investment in machinery and equipment. As we move toward the upper quantiles, this effect diminishes progressively, reaching values close to zero in the 0.75 quantile. This pattern is consistent with diminishing marginal returns to capital and suggests that low-productivity family farmers remain far from the technological frontier, while high-productivity units already operate with more complete capital bundles, leaving *little room* for additional productivity gains.

The declining importance of capital and improvements across the productivity distribution have important implications for climate sensitivity. Since capital intensity, mechanization, irrigation, soil correction and other technological interventions are known to reduce the dependence of output on climatic conditions, the high responsiveness to capital observed in the

lower quantile suggests that these producers are structurally more vulnerable to climate shocks. Conversely, high-productivity family farmers already possess the technological means that buffer climatic variability, producing a lower elasticity of productivity both to capital and to climate. This reinforces the interpretation that climatic impacts are heterogeneous within FF and that the productive structure also shapes exposure to climate risks.

Based on the baseline model results, which demonstrate the effects of climate on land productivity, we projected the impacts of climate change on FF land productivity by productivity quantile. Using [equation \(12\)](#), 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 \(13\)](#) 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 climate projections (2021–2050) represent deviations from the long-term (1971–2005) climatological normal, while the 2017 Census reflects current productive conditions. Our simulations therefore compare today's agricultural structure with future climatic regimes in a static counterfactual framework. The estimates should not be interpreted as extensions of recent trends or as dynamic adaptive responses, but rather as mechanical projections of how the existing production configuration would perform under long-run climatic changes.

All estimates reported in this section refer exclusively to FF establishments as defined by the 2017 Agricultural Census. The regional projections therefore represent differences in climate impacts within the FF sector, and the quantile regressions capture the heterogeneity of climatic sensitivity across productivity levels inside this group. 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 1](#) presents the projected productivity impacts for the 0.25 quantile by federal unit.

The results for the lower productivity quantile (0.25) 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 2](#) presents the projected impacts of climate change on average agricultural productivity for the 0.50 quantile.

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

Table 1. Projected impacts of climate change on land productivity in the lower quantile per hectare (cumulative change, 2021–2050) (0.25 quantile)

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%
Stop	−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(s): Prepared by the authors

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 3 presents the projected impacts of climate change on the productivity of the upper quantile (0.75).

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), Féres *et al.* (2009) and Pinto *et al.* (2008). This pattern is primarily associated with higher temperature increases and reduced precipitation in these regions.

Table 2. Projected impacts of climate change on median land productivity per hectare (cumulative change, 2021–2050) (0.50 quantile)

Federal unit	RCP 4.5 Average change	Standard deviation	Confidence interval (95%)		RCP 8.5 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%
Stop	−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(s): Prepared by the authors

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 regions. 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. [Table A2](#) in the [Supplementary Material](#) presents the results from an aggregated regional perspective.

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,

Table 3. 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%
Stop	−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%
Goiás	3.4%	0.191	0.7%	6.2%	5.3%	0.217	2.2%	8.4%

Source(s): Prepared by the authors

particularly those with higher productivity levels, are less vulnerable to climate phenomena. Additionally, the projections support the findings of [De Paula \(2020\)](#), which also indicate that less productive farmers in the North region experience greater negative impacts.

A clear pattern of impacts emerges across FF 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 9.4% decline, intermediate-productivity farmers face a 5% decline 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%. See [Table A2](#) in the [Supplementary Material](#) for the results.

The projections are consistent with those of [Assunção and Chein \(2016\)](#) in terms of the spatial gradient of climate impacts, with stronger losses in the North, Northeast and Midwest and productivity gains in the South. However, by applying quantile regressions and focusing specifically on FF, we uncover substantial heterogeneity across the productivity distribution

that is not captured in average-effect models. This result aligns with the broader Brazilian literature (e.g. [Féres et al., 2009](#); [Bragança, 2015](#); [Miyajima, 2018](#); [De Paula, 2018](#)) but adds a new distributional dimension by showing that low-productivity family farmers exhibit significantly greater climate sensitivity than higher-productivity units.

The greater sensitivity of less productive FF to the effects of climate change may lead in 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 FF 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. 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 participation levels in the country.

The vulnerabilities of FF 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 Northeast and North have a higher concentration of subsistence-oriented farmers. The share of production destined for on-farm consumption reaches 62% in the Northeast and 30% in the North, compared with lower levels in the Midwest (28%), Southeast (24%) and South (19%). These figures indicate that FF in the North and Northeast has a higher portion of the production destined for self-consumption, and the Northeast remains predominantly subsistence-oriented, while in the other regions it is largely market-oriented ([IBGE, 2019](#)).

As noted by [Garcia and Buainain \(2024\)](#), a large portion of family farmers, even when eligible for public agricultural support programs such as PRONAF [3] and the ABC + Plan [4], 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, is imperative to address the productive and regional specificities of family farmers to reduce their vulnerability, as argued by [Garcia and Buainain \(2024\)](#).

In conclusion, the results suggest that, holding structural factors constant, climate change tends to disproportionately affect less productive farmers. In the modeling, the structural factors are implicitly reflected in the 2017 database, and their evolution is not modeled. The estimates represent the isolated contribution of climate under current conditions. We highlight that public policies targeting FF should account for these differential climate impacts, in

addition to addressing broader constraints related to financing, technical assistance and access to technology.

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 a 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 & Adger, 2000; Kirsch & Schneider, 2016).

5. Final considerations

This study aimed to assess the impacts of climate change, through RCP4.5 and RCP8.5 scenarios [5], on FF land productivity in Brazil, focusing on two key aspects: (1) the productive structure of family farmers, given the significant heterogeneity in farmer profiles across the country, and (2) the spatial variability of climatic effects, which also differs across Brazilian 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 suggest 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, since interventions aimed at expanding infrastructure, mechanization and capital use would generate disproportionately larger productivity gains among low-productivity family farmers, who remain far from the technological frontier. In this regard, low-productivity family farmers have greater potential for adaptation, as they possess more flexibility 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 FF 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.

Notes

1. The World Meteorological Organization (WMO) establishes a minimum standard of 30 years for climate change analysis. This period, known as climatological normal, serves as a 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.
2. In the Supplementary Material, [Table A1](#) presents the results of the baseline model, and [Tables A3](#) and [A4](#) present estimation statistics.
3. The 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).
4. 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, 2023).

5. Although the most recent SSP/CMIP6-based climate projections do not diverge substantially from the RCP/CMIP5 scenarios for horizons up to 2050, future research will incorporate updated climate projections.

Supplementary material

The supplementary material for this article can be found online.

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