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ORIGINAL ARTICLE

New evidence of the driving forces behind Brazil's agricultural TFP growth—A stochastic frontier analysis with climatic variables and land suitability index

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Abstract

Using panel data from 510 Brazilian micro-regions in three census years (1995, 2006 and 2017), this study presents a productivity decomposition for the Brazilian agricultural sector using stochastic production frontier methods that account for the effects of rainfall, temperature and the land suitability index. We also calculated the total factor productivity (TFP) index and decomposed it into technical efficiency, technological change, scale efficiency and environmental efficiency. This article thus provides a new and more realistic assessment of recent Brazilian agricultural productivity growth. In recent decades, Brazilian agriculture has become widely known for presenting fast productivity growth; however, our results suggest that a lower TFP growth rate than previous estimates (1.96% per annum) and the overall effects of climate change could potentially compromise Brazilian agricultural TFP growth in the long run. Our findings might thus generate insights for agricultural and regional policies to increase efficiency in the sector and promote sustainable agricultural development in Brazil, which will contribute to the sector's competitiveness in international markets, the country's social and economic welfare, and environmental conservancy.

KEYWORDS

agricultural TFP, Brazil, environmental conservancy, stochastic production frontier

JEL CLASSIFICATION

O1, O13, Q1

1 | INTRODUCTION

Agricultural productivity growth plays an essential role in economic development in both the short and long term. It provides food security, especially in poorer countries, and as Fuglie (2018) demonstrated, no evidence of a global slowdown in agricultural land, labour and total factor productivity (TFP) growth rates has been identified in the current literature. According to Fuglie et al. (2020), instead of increasing agricultural output through the expansion of land, irrigation or other inputs, most of the growth in the sector is due to the increase in TFP. Alston (2018) found that in recent decades TFP performance has been a consequence of investments in agricultural science and technology, the generation of knowledge and education, improvement in the quality of inputs and labour force qualification.

For Latin America and the Caribbean, Nin-Pratt et al. (2015) estimated that regional agricultural output per worker and TFP increased by 82% and 45%, respectively, in the period 1980–2012 and concluded that this was the result of fast growth in the use of fertiliser, land productivity and capital. This growth allowed the region to reduce the gap between regional TFP with OECD countries. Following Fuglie et al. (2020) and Alston (2018), Nin-Pratt et al. (2015) suggested that the allocation of resources to agricultural research and development (R&D) was a relevant source of the sector's performance, despite uneven attainment across countries.

In this context, Brazil plays a key role in Latin America's total agricultural output and global commodities markets.[1] Nin-Pratt et al. (2015) showed that Brazil represented 46% of regional production in 2010. For the period 1981–2012, they estimated an average annual growth of agricultural output and TFP of 5.1% and 2.5%, respectively. Similarly, other studies estimated the Brazilian agricultural TFP growth as 3.53% per year from 1975 to 2014 and 4.03% per year from 2010 to 2014 (Gasques et al., 2014, 2016).[2]

The discussion surrounding agricultural production and productivity improvements in Brazil often raises concerns about environmental protection. Marin et al. (2022) looked into how Brazil could increase soybean production without increasing deforestation and discovered that if the current trends in soybean yield and cultivated area continue, an extra 5.7 million hectares of forests and savannahs could be transformed into agricultural land over the next 15 years. To tackle this land conversion challenge, they proposed that raising yields and expanding soybean cultivation to regions where livestock farming is practised could effectively boost soybean production across the country without resorting to deforestation.

As Fuglie (2018) argued, increasing agricultural productivity growth is essential to reduce the amount of labour, land and other resources allocated to produce food. In the Brazilian context, this relates to regional agricultural production profile changes and their impacts on environmental sustainability. Vieira Filho (2016) observed that in the last four decades the agricultural frontier expansion was driven towards the MATOPIBA region,[3] where soybean, corn and cotton production have shifted first from the South to the Centre-West and recently to the MATOPIBA region following planting technological innovations. The persistence of this trend hinges on stable weather conditions. Zilli et al. (2020) conducted climatic scenario projections using a spatial partial equilibrium global land use model and estimated a decline in soybean and corn production in the MATOPIBA region;

[1]For example, Stabile et al. (2020) found that Brazil accounted for 30% and 15% of the world soybean and beef production, respectively, in 2013.

[2]As a comparison, Sheng et al. estimated that China's agricultural TFP growth rate was 2.4% in 1992–2009 and verified a slow-down in growth after that year, followed by a gradual recovery after 2012.

[3]The Brazilian Agricultural Research Corporation (Embrapa) defines MATOPIBA as a region formed by areas of the Cerrado biome within the states of Maranhão (MA), Tocantins (TO), Piauí (PI) and Bahia (BA), towards which agricultural production expanded from the second half of the 1980s (https://www.embrapa.br/en/tema-matopiba).

they emphasised the role of rapid productivity growth in mitigating the adverse effects of ongoing climate change on these crops.

Ferreira Filho et al. (2015) employed a dynamic multiregional computable general equilibrium model to simulate land use changes in Brazil from 2005 to 2025. Their findings revealed that imposing limits on deforestation did not undermine Brazil's agricultural supply capacity. Instead, they identified an opportunity to convert low-yield pasture lands into croplands and proposed that externally driven productivity enhancements could help alleviate deforestation pressures. Relatedly, Koch et al. (2019) compiled a panel dataset covering agriculture and deforestation in the Brazilian Amazon for the period 2004–2014. Contrary to assumptions of trade-offs, their analysis showed no substantial evidence supporting conflicts between agriculture and forest conservation. Municipalities that witnessed reduced deforestation also experienced simultaneous growth in cattle production and productivity (cattle per hectare). They also concluded that in regions where there are large yield gaps and technologies for increasing yields are available, constraints on agricultural expansion promoted by forest conservation policies may induce agricultural intensification.

Table 1 presents the share of the production for selected crops (cotton, coffee, sugarcane, corn and soybean) for the five Brazilian geographical regions in 1995, 2006, 2017 (the last three census years) and 2021. Indeed, it is remarkable how the Middle-West region raised its share of total cotton, corn and soybean production from 1995 to 2017, while the Southeast region maintained its share of coffee and sugarcane production. At the same time, the North region increased its share of corn and soybean production from 2.6% and 0.2% in 1995 to 4.8% and 5.5% in 2017, respectively. As argued by Vieira Filho (2016), because the agricultural frontier is

TABLE 1 Share of selected crops in Brazilian regions.

Year	Crop	North	Northeast	Southeast	South	Middle-West
1995	Cotton	2.0%	11.9%	25.1%	36.8%	24.3%
	Coffee	10.3%	5.5%	81.7%	1.1%	1.4%
	Sugarcane	0.2%	20.0%	66.2%	7.1%	6.4%
	Corn	2.6%	6.7%	22.3%	51.2%	17.2%
	Soybean	0.2%	4.9%	9.3%	46.7%	39.0%
2006	Cotton	0.0%	30.6%	8.4%	0.8%	60.2%
	Coffee	3.8%	6.1%	83.6%	5.3%	1.2%
	Sugarcane	0.3%	13.2%	69.7%	7.5%	9.4%
	Corn	2.6%	7.4%	22.6%	43.7%	23.7%
	Soybean	2.4%	6.6%	7.8%	33.8%	49.4%
2017	Cotton	0.6%	24.0%	2.2%	0.0%	73.2%
	Coffee	5.4%	6.0%	85.2%	2.5%	0.9%
	Sugarcane	0.6%	6.6%	69.2%	5.5%	18.1%
	Corn	2.8%	6.4%	12.2%	27.2%	51.3%
	Soybean	4.4%	8.3%	7.5%	35.2%	44.6%
2021	Cotton	0.1%	23.6%	2.1%	0.0%	74.2%
	Coffee	5.8%	7.0%	84.6%	1.8%	0.8%
	Sugarcane	0.5%	7.6%	67.1%	5.4%	19.4%
	Corn	4.8%	9.3%	11.9%	19.1%	54.9%
	Soybean	5.5%	9.5%	8.3%	31.1%	45.6%

Source: IBGE (https://sidra.ibge.gov.br/pesquisa/pam/tabelas) and authors' elaboration.

close to the Amazon region, environmental sustainability issues emerge that reinforce the role of productivity gains through land-saving technological innovations.

The extant literature examining Brazilian agriculture TFP growth and its determinants is relatively large. Helfand and Levine (2004), Helfand et al. (2015), Gasques et al. (2016) and Nin-Pratt et al. (2015) each provide agricultural TFP growth rate estimates. Figure 1 depicts Brazilian agriculture TFP growth (g) between 1975 and 2019 ($g = 2.96\%, p - \text{value} < 0.001, R^2 = 0.98$). From 1975 to 1996, the annual average TFP growth rate was 2.23%, and between 1997 and 2019 it was 3.28%. Figure S1 presents the smoothed estimated kernel densities for Brazilian agricultural TFP growth in both periods.

Brazilian agricultural TFP growth has not been homogenous across farm sizes. Lázari and Magalhães (2019) decomposed the agricultural TFP in the Brazilian Southeast region according to five farm-size classes and found that larger size classes (100–500 ha and above 500 ha) had higher TFP growth than the smaller classes (0–5, 5–20 and 20–100 ha). Complementarily, Helfand et al. (2015) concluded that 'the patterns of farm-size-specific performance in Brazil varied tremendously across regions. In Brazil's North, TFP growth declined with size, in the Centre-West it increased with size, and in the South, it mirrored the U-shaped national distribution' (p. 50).

Labour and land-saving innovations appear to be the sources of Brazilian agricultural TFP growth and were promoted by public and private investments in R&D. Brigatte and Teixeira (2011) analysed the period 1974–2005 and found that investments in infrastructure for transport, energy, research, agricultural irrigation, storage, rural credit and labour force education were the main determinants of the sector's economic growth. Gasques et al. (2021) estimated a huge positive impact on productivity growth resulting from the exchange ratio, followed by spending on research, exports and rural credit on Brazilian agricultural TFP growth in the period 2000–2019.

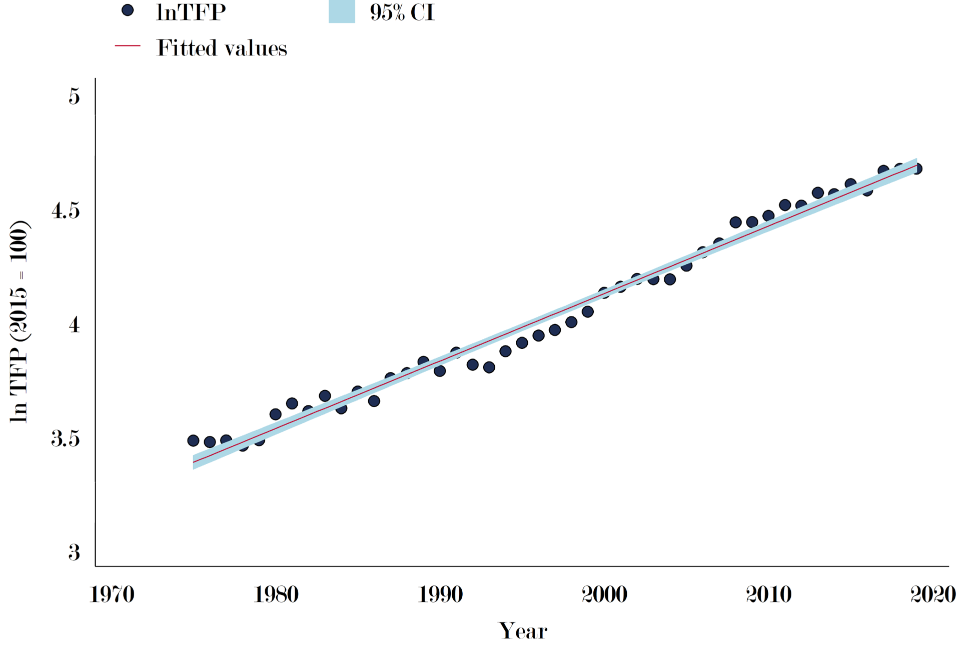

FIGURE 1 Brazilian agriculture total factor productivity (TFP) index (2015 = 100)—1975 to 2019. *Source*: USDA (https://www.ers.usda.gov/data-products/international-agricultural-productivity/) and authors' elaboration. [Colour figure can be viewed at wileyonlinelibrary.com]

These studies on Brazilian agricultural growth discussed aggregated data, however, and did not account for the environmental effects. The main contribution of this article is to produce a TFP growth decomposition of Brazilian agriculture at the micro-regional level, and our approach differs from previous studies in its examination of the potential impacts of climate variables and agricultural suitability on the country's agricultural TFP. We used the same approach as Chambers and Pieralli (2020), in the sense that we implemented a TFP growth accounting procedure to investigate the impact of weather variables on agricultural TFP.

Lachaud et al. (2022) estimated the economic effects of climate change on agricultural productivity in Latin America and the Caribbean, because many studies have reported the challenges imposed by climate change on agricultural productivity. They found that changes in temperature and rainfall patterns from 1961 to 2014 induced significant reductions in TFP growth. Plastina et al. (2021) also presented results that highlighted the importance of explicitly accounting for weather effects in the estimation of TFP growth and its components, because omission of such effects was biased towards TFP growth decomposition.

The findings of this paper complement the literature on TFP issues in Latin America—and more specifically in Brazil—by analysing the agricultural TFP growth at the micro-region level on the following components: shifts in the production frontier due to the application of new processes and systems in the production process; output-oriented scale-and-mix efficiency; fluctuations in productivity associated with economies of scale; movements in productivity due to environmental factors; output-oriented technical efficiency index; and the statistical noise index (SNI). To implement the proposed analysis, we used panel data from 510 Brazilian micro-regions in the last three census years (1995, 2006 and 2017) published, combined with climate data[4] and a land suitability index.[5]

The remainder of this article is structured as follows: Section 2 presents the empirical model and data, followed by Section 3, which contains the results and discussion. Section 4 concludes the paper.

2 | EMPIRICAL MODEL AND DATA

The empirical model estimated in this paper allows us to address the role of the production environment and other managerial techniques in driving productivity growth. Some other examples of early contributions that measured and explained changes in TFP are O'Donnell (2018), Njuki et al. (2018), Lachaud and Bravo-Ureta (2020), and Lachaud et al. (2022). Njuki et al. (2018) defined the period-t technology set in the environment z as:

$$T^t\,(z) = \left\{ (x, q) \in \Re_+^{M+N} : x \text{ can produce } q \text{ in environment } z \text{ in period } t \right\} \tag{1}$$

Following O'Donnell (2018) and Njuki et al. (2018), we make the assumption that the TFP index is a multiplicative index that compares the productivity of firm i in period t with the productivity of firm k in period s. Thus, the multiplicative output and input indices ($Q\left(q_{it}\right)$ and $X\left(x_{it}\right)$, respectively) are constructed using aggregator functions that take the form:

$$Q\left(q_{it}\right) \propto \prod_{n=1}^{N} q_{n_{it}}^{a_n}$$

[4] Figures S2 and S3 show the smoothed estimated kernel densities for temperature and rainfall index in the periods 1980–1999 and 2000–2016.

[5] The agricultural suitability index was drawn from Sparovek et al. (2014), which ranks land according to whether it possesses soil and climatic conditions advantageous for the non-irrigated cultivation of annual and perennial crops. The suitability was spatialized with a range from 0 to 1, where 0 indicates a condition unsuitable for agricultural activities and 1 a condition of maximum fitness. Figure S4 shows the regional distribution for agricultural suitability in Brazil.

$$X\left(x_{it}\right) \propto \prod_{n=1}^{N} x_{m_{it}}^{b_m}$$

where $a_1, \ldots, a_n$ are non-negative output weights that sum to one, and $b_1, \ldots, b_m$ are non-negative input weights that sum to one (i.e., $\sum_{m=1}^{M} b_m = 1$).

According to O'Donnell (2018), productivity growth is measured and tracked using a TFP index (TFPI). A TFP index is any variable of the form $\text{TFPI}^M\left(x_{ks}, q_{ks}, x_{it}, q_{it}\right) = \left[Q\left(q_{it}\right) / X\left(x_{it}\right)\right] / \left[Q\left(q_{ks}\right) / X\left(x_{ks}\right)\right]$, where $Q(.)$ and $X(.)$ are non-negative, nondecreasing and linearly homogeneous aggregator functions.

Following O'Donnell (2018) and Njuki et al. (2018), the TFP is a multiplicative TFP index defined as:

$$\text{TFPI}\left(x_{ks}, q_{ks}, x_{it}, q_{it}\right) = \frac{q_{it}}{q_{ks}} \prod_{m=1}^{M} \left(\frac{x_{mks}}{x_{mit}}\right)^{b_m} \tag{2}$$

One of the main production heterogeneities in Brazilian agriculture is the different levels of mechanisation among farms: very large, capital-intensive (CI) farms co-exist with smaller labour-intensive (LI) farms, and the level of mechanisation has grown over the last decades.[6] We therefore decided to consider a flex-frontier to incorporate production heterogeneity among the regions in the analysis, classifying each micro-region as CI or LI using the following empirical threshold: We estimated the average capital-labour ratio (CLR) from the total sample and set the average as the threshold. A micro-region i in time t was then classified as CI if its CLR was above the average; otherwise, it was classified as LI.[7] The SPF model can be expressed as follows:

$$\begin{aligned} \ln y_{it} = \quad & \phi_0 + \sum_{s=1}^{26} \phi_s^k S_s + \sum\nolimits_k^{\text{CI, LI}} \lambda^k T + \sum\nolimits_k^{\text{CI, LI}} \sum_{m=1}^{M} \beta_m^k \ln x_{mit} \\ & + \sum\nolimits_k^{\text{CI, LI}} \sum_{j=1}^{J} \rho_j^k z_{jit} + \sum\nolimits_k^{\text{CI, LI}} \sum_{n=1}^{N} \gamma_n^k d_{nit} + v_{it} - u_{it} \end{aligned} \tag{3}$$

where $\ln y_{it}$ is the log of output; x_{mit}, z_{jit} and d_{nit} represent vectors of conventional inputs (capital, labour and land) of micro-region i on time t (i.e., input m of micro-region i on time t), characteristics of the production environment (characteristic j of micro-region i on time t) and climate variables (climate variable n of micro-region i on time t); v_{it} and u_{it} are a statistical error term and an inefficiency component with distributional assumptions $v_{it} \sim N\left(0, \sigma_v\right)$ and $u_{it} \sim N^+\left(0, \sigma_u\right)$, respectively. We also included a time-trend variable to allow the technical efficiency to vary over time[8]—that is, $\sigma_u = \exp\left(\theta_0 + \theta_1 t\right)$. The parameter ϕ_0 represents the linear coefficient adjusted by the vector of state-dummy variables (S) for the 27 Brazilian states analysed to capture time-invariant unobserved heterogeneity that affects production technology, T is a time trend that captures technological progress, and $\lambda^k, \beta_m^k, \rho_j^k$ and γ_n^k are parameters to be estimated for each k ($k = \text{CI, LI}$) group of micro-regions. Based on Njuki et al. (2018), any observation-invariant non-negative weights that sum to one can be used to compute the TFP index. Using the same procedure as those authors, we considered $b_m = \frac{\widehat{\beta_m^k}}{\sum_{m=1}^{M} \beta_m^k}$, where $\widehat{\beta_m^k}$ is an estimator of β_m^k according to Equation (3).

[6]Felema and Spolador (2022) demonstrated the role of rising mechanization on the agricultural output growth between 1995 and 2017 and the continued persistence of regional and intraregional differences in the Brazilian agricultural sector.

[7]Figure SA5 demonstrates the clear heterogeneity between the North-Northeast and Center-South regions in terms of production factor intensity in agriculture, and there is no significant difference in micro-regions classification over the period.

[8]See Kumbhakar et al. (2014).

Njuki et al. (2018) presented a complete specification of the multiplicative index that allows comparison of the TFP of micro-region i at time t with the TFP of micro-region h at time s. From Equation (3), this is represented as follows:

$$\begin{aligned}&\mathrm{TFPI}(x_{hs}, q_{hs}, x_{it}, q_{it}) = \\ &= \left(\frac{\exp(\lambda_t)}{\exp(\lambda_s)}\right)\left[\prod_{m=i}^{M}\left(\frac{x_{mit}}{x_{mhs}}\right)^{\beta_{km}-b_{km}}\right]\left[\left(\frac{\exp(\phi_i)}{\exp(\phi_h)}\right)\frac{\exp\left(\sum_{j=1}^{J}\rho_{kj}z_{jit}\right)}{\exp\left(\sum_{j=1}^{J}\rho_{kj}z_{jhs}\right)}\right]\left[\frac{\exp\left(\sum_{n=1}^{N}\gamma_{kn}d_{nit}\right)}{\exp\left(\sum_{n=1}^{N}\gamma_{kn}d_{nhs}\right)}\right]\times \\ &\times\left[\frac{\exp(-u_{it})}{\exp(-u_{hs})}\right]\left[\frac{\exp(v_{it})}{\exp(v_{hs})}\right]\end{aligned} \quad (4)$$

The multiplicative TFP index defined in Equation (4) consists of the following components[9]: $\left(\frac{\exp(\lambda t)}{\exp(\lambda s)}\right)$ is the technology index (TI), which measures any shifts in the production frontier due to the application of new processes and systems in the production process; $\left[\prod_{m=i}^{M}\left(\frac{x_{mit}}{x_{mhs}}\right)^{\beta_{km}-b_{km}}\right]$ is the component defined as OSEI and captures fluctuations in productivity associated with economies of scale; $\left[\left(\frac{\exp(\phi_i)}{\exp(\phi_h)}\right)\frac{\exp\left(\sum_{j=1}^{J}\rho_{kj}z_{jit}\right)}{\exp\left(\sum_{j=1}^{J}\rho_{kj}z_{jhs}\right)}\right]$ is the output-oriented production environment index (OPEI) or a measure of production environment changes. This index is related to the production profile as the shares of perennial and temporary crops, extractive activities and unobserved time-invariant effects at the state level; $\left[\frac{\exp\left(\sum_{n=1}^{N}\gamma_{kn}d_{nit}\right)}{\exp\left(\sum_{n=1}^{N}\gamma_{kn}d_{nhs}\right)}\right]$ is the environmental variables index (OEI) that captures movements in productivity due to environmental factors (e.g., rainfall, temperature, soil type and topography); $\left[\frac{\exp(-u_{it})}{\exp(-u_{hs})}\right]$ is defined as an OTEI that measures movements towards or away from the frontier due to managerial performance; and $\left[\frac{\exp(v_{it})}{\exp(v_{hs})}\right]$ is the statistical noise index.

Data from the empirical model were drawn from three databases. The first is the Agricultural Censuses of1995, 2006 and 2017 (the most recent yearbook published), conducted by the Brazilian Institute of Geography and Statistics (IBGE). Data on output and conventional agricultural inputs obtained from IBGE are the agricultural output value ((R$ thousands) - Official exchange rate (R$/US$) in 2022 was 5.16397according to the World Development Indicators (https://databank.worldbank.org/source/world-development-indicators#)),[10] capital stock (total number of tractors), labour (workers employed in agriculture) and land (cultivated land for permanent crops and temporary crops, both in hectares). Because the Agricultural Census of 1995 does not have information about capital stock, we estimated the trend for capital from 2006 to 2017, and based on the estimated growth rate, we implemented a retropolation method to obtain the values for 1995. Finally, we added a slope-dummy variable associated with capital stock-denominated *SDK* in the empirical model; as we have a flex-frontier, there is a slope-dummy coefficient for each group of micro-regions (CI and LI).

The second source is the Xavier et al. (2015) database, where we collected the annual average temperature and rainfall by day for each micro-region in the years when censuses were conducted. The third source of data is the land suitability index from Sparovek et al. (2014). We have data from 510 micro-regions for each census year, because we used the municipality

[9]A complete theoretical deduction and explanation about the TFP index construction can be found in O'Donnell (2018, pp. 14–51).

[10]The agricultural output corresponds to the sum of total production from extractive crops, perennial crops, temporary crops and forestry. It does not include livestock production.

classification from the last demographic census published by IBGE (2010).[11] Table 2 presents the descriptive statistics of the variables used in the empirical model.

As temperature and rainfall averages may change over the year given the specific climate patterns for each geographical region, our first step was to create seasonal variables. For simplicity, we divided the seasons according to the annual calendar. That is, season 1 represents summer–autumn in the Southern Hemisphere and corresponds, in this paper, to the months from January to June; season 2 thus corresponds to winter–spring (July to December).

Because some crops are inter-annual, we adopted the 2-year average for seasonal temperature and rainfall in both the year of each census and the year prior. Some weather data were unavailable for 2017, so there is no information for rainfall and temperature in the last year's quarter. However, the empirical model can be estimated without further issues, because we used the 2-year average strategy.[12]

Considering that agricultural censuses separate the total output according to different productive profiles, in this paper we include the shares of total production from extractive crops (%EC), perennial crops (%PC) and temporary crops (%TC) in each micro-region in the empirical model, and left the share of forestry (%FC) output as the baseline. Finally, we added binary variables for each state, the estimated parameters of which indicate the unobserved non-stochastic time-invariant characteristics of the production environment.

3 | RESULTS AND DISCUSSION

The regression results corresponding to specifications (3) and (4) are presented in Tables 3 and 4, respectively. The estimated coefficients for capital, labour and land are non-negative and statistically significant at the 5% level and are interpreted as input elasticities.

Similarly, the estimated coefficients during both climate seasons are also statistically significant. This indicates that rainfall positively contributes to agricultural output. Instead, rising temperatures, specifically in the summer–autumn season, decrease output, because this is the harvest time for some of the most important Brazilian crops (soybean, corn, cotton, rice and so on). Overall, the estimated effects of the temperature and rainfall variables in each semester show opposite signs to the first-order and quadratic variables. For instance, augmenting rainfall during the first and second semesters exhibits positive marginal impacts on production; nevertheless, their quadratic counterparts yield negative effects. This implies that these positive outcomes are greater when the baseline rainfall level is low, and further increases in rainfall beyond this point could potentially diminish production.[13] Instead, considering temp_{s1} for CI technology, increasing temperature reduces the output when average temperatures are low; however, the effects are positive when the baseline temperature is high. In the Table S1 and Figure S6, we presented the descriptive statistics of the weather effects and their distribution across the Brazilian states. In general, the highest estimated temperature effects are concentrated in the Centre-West region (except in 2017, when more intensive estimated effects are verified in the North and Northeast regions), while the highest estimated rainfall effects are observed in the Northeast region.

[11]There were 4947 municipalities in 1995, 5534 in 2006 and 5546 in 2017. On average, there were 9.7, 10.8 and 10.9 municipalities in each micro-region in 1995, 2006 and 2017, respectively. The number of micro-regions is constant over time.

[12]In this case, note that variable Rain (sem. 2) for 2017 is calculated using data on 9 months (July to December 2016 and July to September 2017).

[13]For instance, note that the marginal effect of rain_{s1} considering CI technology is: $\frac{d\ln y}{d\text{rain}_{s1}} = \gamma_5^{CI} + 2\gamma_7^{CI} \times rain_{s1}$. From the estimated values for temp_{s1}, temp_{s2}, rain_{s1}, rain_{s2}, $(\text{temp}_{s1})^2$, $(\text{temp}_{s2})^2$, $(\text{rain}_{s1})^2$ and $(\text{rain}_{s2})^2$, we computed the marginal effect of temperature (MET) and the marginal effect of rainfall (MER) for each region i in time t. Because all MET values are negative, we give the spatial distribution of MET in absolute values to present an intuitive illustration to the reader.

TABLE 2 Descriptive statistics.

Variable	Proxy	Source	*N*	Mean	SD
CI					
Output	Total production (1000 R$)	IBGE	835	833,508.20	1,036,422.00
Capital	Total tractors	IBGE, with adjustments	835	2807.50	2653.33
Labour	Total workers	IBGE	835	23,629.40	17,100.72
Land	Harvest area (ha)	IBGE	835	323,231.60	385,886.70
Suitability	Land suitability for agriculture	Sparovek et al. (2014)	835	0.38	0.14
SDK	Slope-dummy variable	IBGE, with adjustments	835	2.52	3.67
%EC	Share of extractive crops	IBGE	835	0.01	0.04
%PC	Share of perennial crops	IBGE	835	0.18	0.23
%TC	Share of temporary crops	IBGE	835	0.75	0.26
%FC	Share of forestry crops	IBGE	835	0.06	0.12
Temp. (sem. 1)	Average daily temperature (°C)	Xavier et al. (2015)	835	23.10	2.30
Temp. (sem. 2)	Average daily temperature (°C)	Xavier et al. (2015)	835	22.25	2.88
Rain (sem. 1)	Average daily rainfall (mm)	Xavier et al. (2015)	835	4.61	0.90
Rain (sem. 2)	Average daily rainfall (mm)	Xavier et al. (2015)	835	3.71	0.85
LI					
Output	Total production (1000 R$)	IBGE	695	242,642.50	435,695.80
Capital	Total tractors	IBGE, with adjustments	695	359.84	412.24
Labour	Total workers	IBGE	695	42,938.05	31,838.42
Land	Harvest area (ha)	IBGE	695	245,374.00	270,937.90
Suitability	Land suitability for agriculture	Sparovek et al. (2014)	695	0.33	0.11
SDK	Slope-dummy variable	IBGE, with adjustments	695	1.74	2.60
%EC	Share of extractive crops	IBGE	695	0.07	0.11
%PC	Share of perennial crops	IBGE	695	0.26	0.25
%TC	Share of temporary crops	IBGE	695	0.63	0.25
%FC	Share of forestry crops	IBGE	695	0.04	0.12
Temp. (sem. 1)	Average daily temperature (°C)	Xavier et al. (2015)	695	26.16	1.69
Temp. (sem. 2)	Average daily temperature (°C)	Xavier et al. (2015)	695	25.99	2.39
Rain (sem. 1)	Average daily rainfall (mm)	Xavier et al. (2015)	695	4.81	2.52
Rain (sem. 2)	Average daily rainfall (mm)	Xavier et al. (2015)	695	2.09	1.47

TABLE 2 (Continued)

Variable	Proxy	Source	*N*	Mean	SD
Total					
Output	Total production (1000 R$)	IBGE	1530	565,108.40	871,022.70
Capital	Total tractors	IBGE, with adjustments	1530	1695.65	2324.53
Labour	Total workers	IBGE	1530	32,400.33	26,685.18
Land	Harvest area (ha)	IBGE	1530	287,864.90	340,654.60
Suitability	Land suitability for agriculture	Sparovek et al. (2014)	1530	0.36	0.13
SDK	Slope-dummy variable	IBGE, with adjustments	1530	2.17	3.25
%EC	Share of extractive crops	IBGE	1530	0.04	0.08
%PC	Share of perennial crops	IBGE	1530	0.21	0.24
%TC	Share of temporary crops	IBGE	1530	0.70	0.26
%FC	Share of forestry crops	IBGE	1530	0.05	0.12
Temp. (sem. 1)	Average daily temperature (°C)	Xavier et al. (2015)	1530	24.49	2.55
Temp. (sem. 2)	Average daily temperature (°C)	Xavier et al. (2015)	1530	23.95	3.25
Rain (sem. 1)	Average daily rainfall (mm)	Xavier et al. (2015)	1530	4.70	1.83
Rain (sem. 2)	Average daily rainfall (mm)	Xavier et al. (2015)	1530	2.98	1.42

Note: Temp. (sem. 1) is the 2-year (the census year and the year prior) average temperature between January and June, and Temp. (sem. 2) is the 3-year average temperature between July and December. Rain (sem. 1) and Rain (sem. 2) indicate the 2-year average rainfall in the period January–June and July–December, respectively.

Regarding technical efficiency, production theory states that a micro-region is fully technically efficient and operating on the frontier when the estimated efficiency is at 100%. We found that technical efficiency across the sampled micro-region averaged 70.99%, with ranges between 14.78% and 92.16%.[14] Figure 2 illustrates the kernel density of the technical efficiency distribution.

Results for the TFP index and its decomposition according to Equation (4) are reported in Table 4. The index numbers in any given row are the micro-region averages for each state considering the three census years analysed (1995, 2006 and 2017). The relevant quantities for each micro-region studied were compared with the corresponding quantities in Brasilândia (the state of Acre—AC) in 1995. The states of São Paulo (SP), Paraná (PR), Mato Grosso (MT), Rio Grande do Sul (RS), Goiás (GO), Santa Catarina (SC), Mato Grosso do Sul (MS) and Minas Gerais (MG) are historically the most representative, considering the value of Brazilian agricultural production.[15] For all of these states that show a high TFP index on average, the major effect on TFPI comes from the production environment index (OPEI), followed by the technology index (TI).

Figure 3 illustrates the regional distribution of TFPI and its components in 2017. For the TFPI and OSEI indexes, higher values are observed for the Middle-West, Southeast and South

[14]Bragagnolo et al. (2021) found an average technical efficiency of 54.9% in the period 1995–2017. Nin-Pratt et al. (2015) estimated the efficiency growth rate as 1.5% in the period 1981–2012, while our results showed an average percentage growth rate of −0.44% for technical efficiency between 1995 and 2017.

[15]On Figure S5, all of these states are in the group considered capital intensive. The exception is Minas Gerais, where its North region was classified as labour-intensive.

TABLE 3 SFA model results.

Variables	Coefficients	Estimated value	95% CI
Capital-Intensive (CI)			
ln(capital)	β_1^{CI}	0.464****	[0.374, 0.555]
ln(labour)	β_2^{CI}	0.0291	[−0.0726, 0.131]
ln(land)	β_3^{CI}	0.659****	[0.588, 0.730]
SDK	β_4^{CI}	−0.00561	[−0.0312, 0.0200]
ln(suitability)	β_5^{CI}	0.382**	[0.0335, 0.730]
%EC	ρ_1^{CI}	−3.859****	[−5.130, −2.588]
%PC	ρ_2^{CI}	0.517***	[0.137, 0.896]
%TC	ρ_3^{CI}	0.332*	[−0.0137, 0.678]
$temp_{s1}$	γ_1^{CI}	−2.683****	[−3.376, −1.990]
$temp_{s2}$	γ_2^{CI}	2.179****	[1.629, 2.729]
$(temp_{s1})^2$	γ_3^{CI}	0.0573****	[0.0424, 0.0721]
$(temp_{s2})^2$	γ_4^{CI}	−0.0490****	[−0.0609, −0.0372]
$rain_{s1}$	γ_5^{CI}	0.289*	[−0.0124, 0.591]
$rain_{s2}$	γ_6^{CI}	0.453***	[0.125, 0.781]
$(rain_{s1})^2$	γ_7^{CI}	−0.0205	[−0.0502, 0.00931]
$(rain_{s2})^2$	γ_8^{CI}	−0.0653***	[−0.108, −0.0223]
Time-trend	λ^{CI}	0.427****	[0.304, 0.550]
Labour-Intensive (LI)			
ln(capital)	β_1^{LI}	0.0565*	[−0.000123, 0.113]
ln(labour)	β_2^{LI}	0.573****	[0.478, 0.669]
ln(land)	β_3^{LI}	0.465****	[0.385, 0.545]
SDK	β_4^{LI}	−0.0334**	[−0.0662, −0.000552]
ln(suitability)	β_5^{LI}	0.284	[−0.181, 0.749]
%EC	ρ_1^{LI}	−1.808****	[−2.443, −1.172]
%PC	ρ_2^{LI}	0.114	[−0.330, 0.557]
%TC	ρ_3^{LI}	−0.452**	[−0.892, −0.0126]
$temp_{s1}$	γ_1^{LI}	−0.837^{+}	[−1.963, 0.289]
$temp_{s2}$	γ_2^{LI}	0.273	[−0.757, 1.302]
$(temp_{s1})^2$	γ_3^{LI}	0.0206*	[−0.000992, 0.0423]
$(temp_{s2})^2$	γ_4^{LI}	−0.00988	[−0.0297, 0.00993]
$rain_{s1}$	γ_5^{LI}	0.316****	[0.212, 0.419]
$rain_{s2}$	γ_6^{LI}	0.446****	[0.254, 0.639]
$(rain_{s1})^2$	γ_7^{LI}	−0.0146****	[−0.0219, −0.00730]
$(rain_{s2})^2$	γ_8^{LI}	−0.0552****	[−0.0850, −0.0254]
Time-trend	λ^{LI}	0.161**	[0.0343, 0.287]

TABLE 3 (Continued)

Variables	Coefficients	Estimated value	95% CI
State-dummy variables			
AC	—	—	—
AL	γ_1	1.472****	[1.033, 1.912]
AM	γ_2	0.516***	[0.129, 0.904]
AP	γ_3	1.026****	[0.491, 1.560]
BA	γ_4	0.626***	[0.225, 1.026]
CE	γ_5	1.384****	[0.939, 1.830]
DF	γ_6	0.767**	[0.0190, 1.514]
ES	γ_7	0.973****	[0.512, 1.433]
GO	γ_8	0.542***	[0.146, 0.937]
MA	γ_9	0.888****	[0.488, 1.289]
MG	γ_{10}	0.714****	[0.328, 1.100]
MS	γ_{11}	0.156	[−0.274, 0.586]
MT	γ_{12}	0.463**	[0.0570, 0.868]
PA	γ_{13}	0.437**	[0.0500, 0.824]
PB	γ_{14}	1.032****	[0.597, 1.468]
PE	γ_{15}	1.365****	[0.939, 1.790]
PI	γ_{16}	0.699****	[0.299, 1.100]
PR	γ_{17}	0.767****	[0.360, 1.175]
RJ	γ_{18}	0.701***	[0.276, 1.125]
RN	γ_{19}	1.082****	[0.624, 1.539]
RO	γ_{20}	−0.319+	[−0.741, 0.103]
RR	γ_{21}	0.135	[−0.325, 0.595]
RS	γ_{22}	0.820****	[0.395, 1.244]
SC	γ_{23}	0.880****	[0.449, 1.311]
SE	γ_{24}	0.981****	[0.493, 1.468]
SP	γ_{25}	1.091****	[0.692, 1.490]
TO	γ_{26}	0.0898	[−0.320, 0.499]
Constant	γ_0	5.248**	[1.031, 9.465]
ln(usigma)			
t		0.343**	[0.0520, 0.634]
Constant		−2.167****	[−2.982, −1.351]
ln(vsigma)			
Constant		−1.432****	[−1.608, −1.257]
Observations		1530	

Note: 95% confidence intervals in brackets. The estimate of σ_v^2 is recovered by $\sigma_v^2 = \exp(-1.432) = 0.2388$; the same procedure is employed to get the estimate of σ_u^2.

$^+p<0.15$; $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$; $^{****}p<0.001$.

regions, which also corresponds to the regions with more representative agricultural output. This highlights that the Brazilian agricultural frontier is highly productive, and the highest values observed for the OTEI are also in the agricultural frontier regions.

TABLE 4 Average total factor productivity index (TFPI), technology index (TI), OSEI, output-oriented production environment index (OPEI), OEI, OTEI and statistical noise index (SNI) by state.

State	TFPI = (QI/XI)	TI	OSEI	OPEI	OTEI	OEI	SNI
AC	2.14	1.18	1.01	1.13	0.94	1.03	1.59
AL	13.50	1.22	1.01	6.11	0.71	1.01	1.86
AM	4.22	1.18	0.99	1.90	1.07	1.00	1.82
AP	6.84	1.18	0.88	3.30	1.02	0.98	1.87
BA	4.33	1.25	1.09	2.89	0.60	1.02	1.73
CE	3.11	1.18	1.04	5.18	0.29	1.03	1.57
DF	25.37	2.12	1.22	5.60	0.77	1.05	2.16
ES	17.06	1.75	1.14	6.32	0.73	1.03	1.86
GO	18.53	2.12	1.24	4.25	0.57	1.02	2.35
MA	3.40	1.23	1.04	2.71	0.54	1.04	1.65
MG	15.53	1.77	1.10	4.42	0.72	1.03	1.97
MS	16.70	2.12	1.31	2.88	0.64	1.00	2.52
MT	19.48	2.10	1.37	3.66	0.54	1.01	2.50
PA	4.35	1.33	1.08	1.97	0.91	1.00	1.93
PB	3.29	1.18	0.97	3.51	0.42	1.02	1.59
PE	7.62	1.20	1.01	5.52	0.57	1.01	1.66
PI	2.27	1.21	1.04	2.28	0.32	1.02	1.90
PR	22.32	2.12	1.30	5.34	0.70	1.05	2.16
RJ	14.57	1.97	0.96	4.87	0.73	1.00	2.30
RN	4.49	1.27	1.00	4.37	0.37	1.02	1.84
RO	5.25	1.62	1.12	1.30	0.88	1.03	1.96
RR	3.62	1.28	0.96	1.79	0.82	1.01	1.98
RS	19.36	2.12	1.26	5.62	0.61	1.04	2.21
SC	18.19	2.11	1.19	5.68	0.63	1.03	2.21
SE	5.32	1.18	1.00	3.91	0.66	1.03	1.58
SP	31.25	2.11	1.18	7.91	0.69	1.03	2.34
TO	6.38	1.89	1.16	2.23	0.49	1.04	2.11

The environmental index was separated into climate and production indexes (OEI and OPEI, respectively). In the studied period, the highest environmental index (OEI) values were in the states of Paraná (PR), Distrito Federal (DF), Rio Grande do Sul (RS), Tocantins (TO) and Maranhão (MA); the highest values of the production environment index (OPEI) were observed for the states of São Paulo (SP), Espírito Santo (ES), Alagoas (AL), Santa Catarina (SC) and Rio Grande do Sul (RS) and Paraná (PR). Figure 3 shows that OPEI is predominantly high in the Southeast and South regions. Figure 4 depicts the relationship among TFPI and the selected environmental variables of land suitability, rainfall and temperature. A stronger correlation is verified between TFPI and rainfall and temperature; these results corroborate the estimations of Lachaud and Bravo-Ureta (2020), who determined that climatic variability (especially an increase in average temperature) negatively affects agricultural production in the context of Latin America and the Caribbean.

The TFPI average annual growth rates (for the period 1995–2017) of its components are reported in Table 5. For example, the TFPI numbers for the state of São Paulo in 1995 and 2017 are 24.4688 and 37.35764, respectively; thus, the state's TFPI average percentage growth

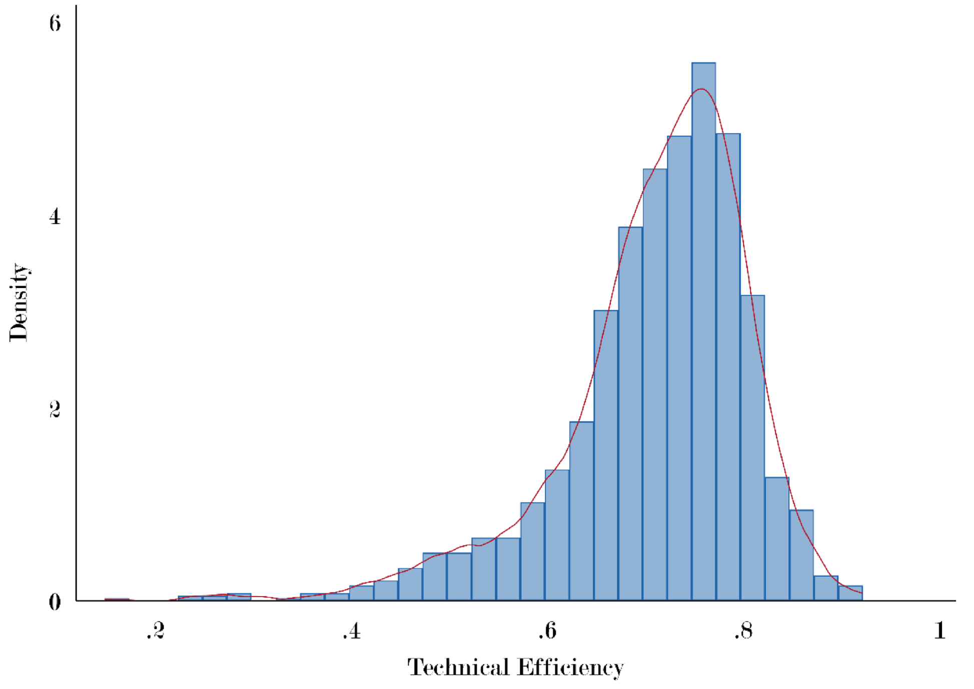

FIGURE 2 Histogram of technical efficiency scores. [Colour figure can be viewed at wileyonlinelibrary.com]

rate was computed as $\left(\frac{37.35764}{24.4688}\right)^{\frac{1}{2017-1995}} - 1 = 1.94\%$. The same procedure was employed for the other index numbers. In the period analysed, Brazilian agricultural TFP increased by 1.96%[16] per annum due to a combination of technical progress (2.62% per annum), scale-and-mix efficiency change (−0.05% per annum), technical efficiency change (−0.44% per annum), production environment change (0.07% per annum), environmental change (−0.75% per annum) and unexplained factors (0.33% per annum). Trindade and Fulginiti (2015) estimated agricultural productivity growth during the period 1969–2009 in South America and observed an average TFP of 2.54% for Brazil in the sub-period 2000–2009. In the period 1975–2006, Bragagnolo et al. (2010) estimated the Brazilian agriculture TFP growth as 3.1% per annum, while Nin-Pratt et al. (2015) estimated a TFP growth rate of 2.5% for the period 1981–2012, and Bragagnolo et al. (2021) estimated a growth rate of 3.03% per annum for the same period (1995–2017).

The highest TFP growth was observed in the state of Tocantins (TO) followed by Mato Grosso (MT), Rondônia (RO), Mato Grosso do Sul (MS) and Goiás (GO). Tocantins and Rondônia are located in the North region, and the other three are located in the Middle-West. The Brazilian agricultural frontier expanded to these states during the 1980s and 1990s,[17] where soybean, corn and cotton were some of the main crops. Figure S7 illustrates how the agricultural frontier regions presented high productivity gains from 1995 to 2017. Our results emphasise the role of technical progress in Brazilian agricultural frontier expansion, which fosters TFP growth and may diminish the pressure over land use change and natural resources.

[16]In all studies mentioned, the methodological approaches are different than those implemented in this article.

[17]For a more detailed analysis of Brazilian agricultural frontier expansion, see Vieira Filho (2016) and Freitas (2022).

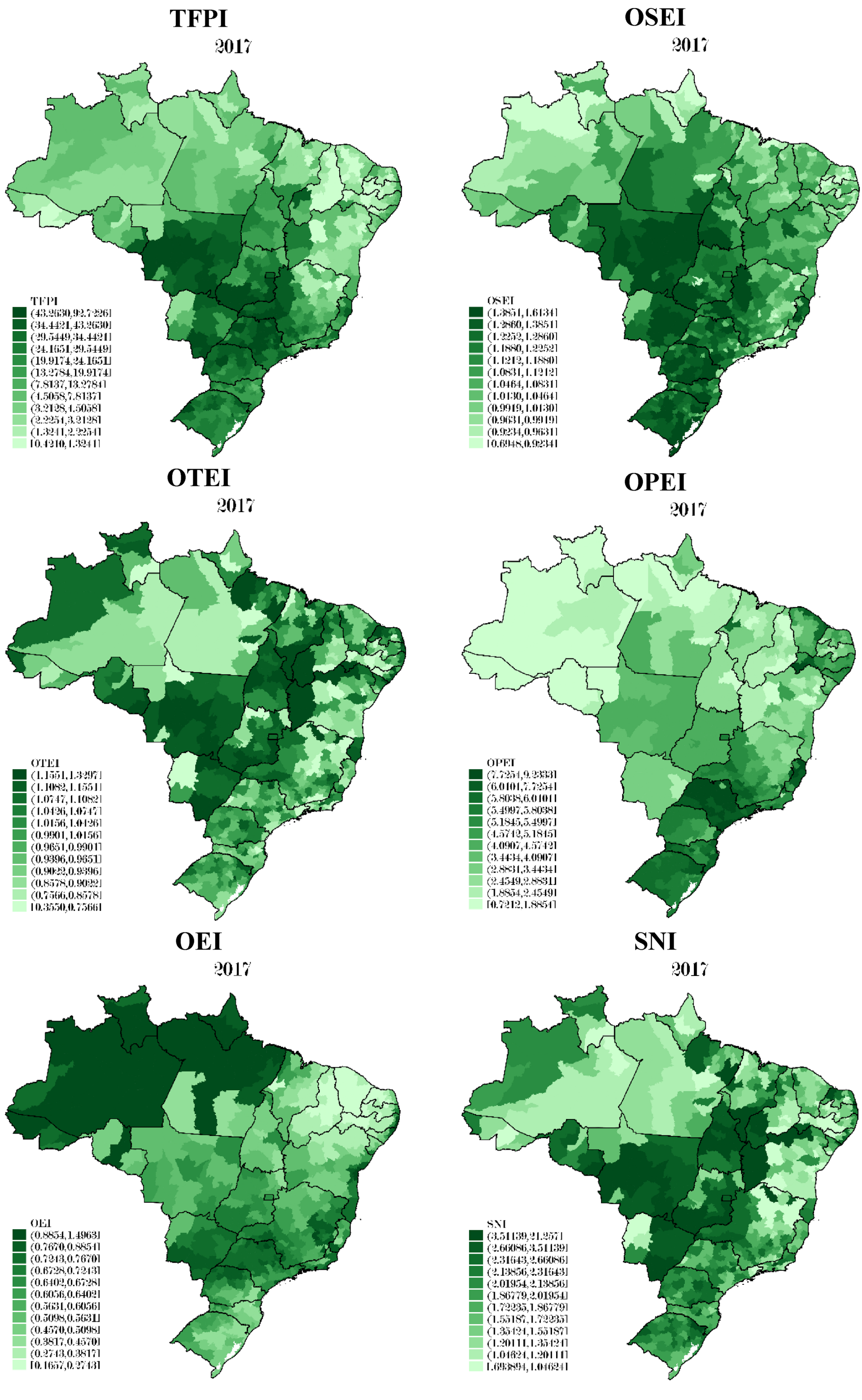

FIGURE 3 Scores of total factor productivity index (TFPI), output-oriented scale and mix efficiency index (OSEI), output-oriented technical efficiency index (OTEI), oriented production environment index (OPEI), output-oriented environmental variables index (OEI) and statistical noise index (SNI) by micro-regions in 2017. [Colour figure can be viewed at wileyonlinelibrary.com]

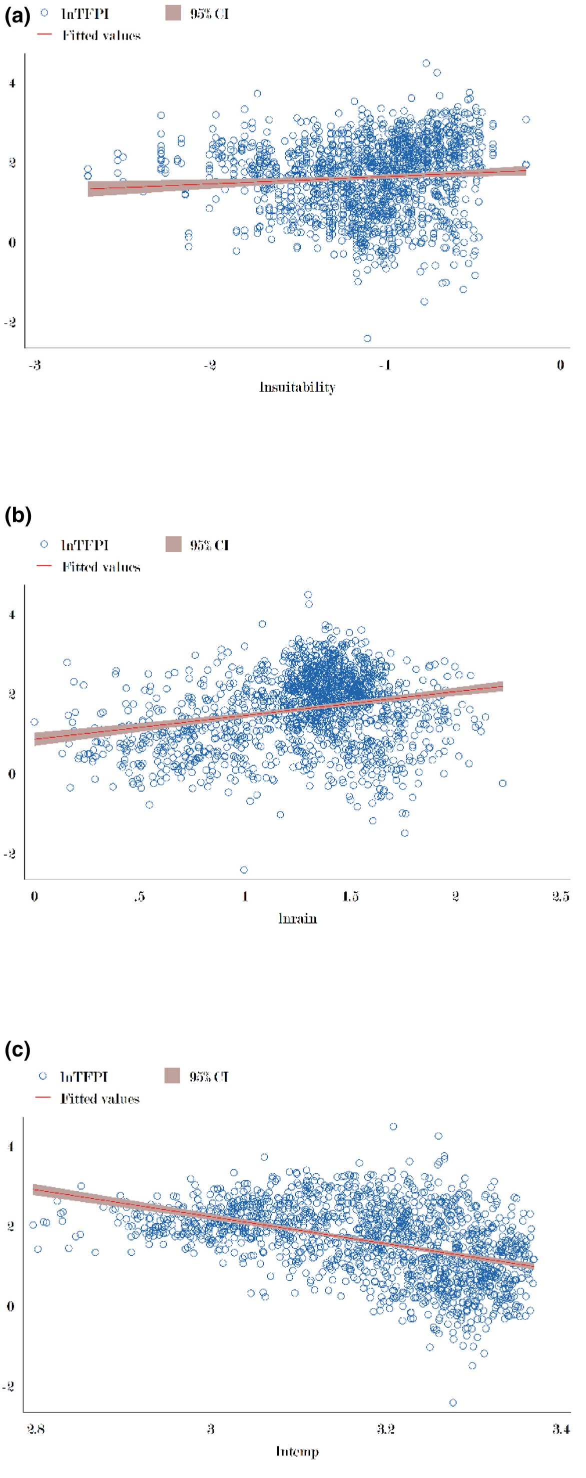

FIGURE 4 Scatterplot for total factor productivity index (TFPI) and (a) land suitability, (b) rainfall and (c) temperature. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Average percentage growth rates by state.

State	%ΔTFPI	%ΔTI	%ΔOSEI	%ΔOPEI	%ΔOEI	%ΔOTEI	%ΔSNI
AC	−1.01%	1.47%	0.13%	0.09%	−1.14%	−0.65%	−1.12%
AL	−3.19%	0.99%	−0.40%	−1.59%	−1.75%	−0.46%	0.93%
AM	−2.62%	1.47%	0.00%	−0.24%	0.17%	−0.93%	−3.19%
AP	−5.30%	1.47%	0.35%	−1.62%	−0.09%	−1.21%	−3.57%
BA	1.36%	1.63%	−0.15%	0.18%	−0.26%	−0.68%	0.90%
CE	−0.24%	1.47%	−0.12%	−0.34%	−2.24%	−0.31%	1.23%
DF	4.06%	3.96%	−0.16%	−0.07%	−1.33%	0.04%	1.64%
ES	1.01%	3.61%	0.29%	0.81%	−0.78%	−0.95%	−1.65%
GO	6.38%	4.01%	−0.05%	0.62%	0.53%	−0.12%	1.14%
MA	3.26%	1.60%	−0.25%	0.44%	−1.47%	−0.02%	2.37%
MG	3.36%	3.60%	0.00%	0.69%	−0.58%	−0.68%	−0.01%
MS	6.82%	3.96%	0.06%	0.36%	1.28%	−0.22%	1.06%
MT	8.99%	4.02%	0.03%	0.80%	0.51%	0.28%	2.65%
PA	3.18%	2.25%	0.02%	1.56%	0.10%	−0.54%	−1.16%
PB	−1.62%	1.47%	−0.18%	−0.48%	−1.65%	−0.86%	−0.67%
PE	−1.38%	1.32%	−0.16%	−0.36%	−1.48%	−0.72%	−0.05%
PI	5.27%	1.33%	−0.09%	−0.44%	−0.92%	−0.26%	3.76%
PR	3.08%	3.96%	−0.05%	0.15%	−0.90%	−0.36%	0.21%
RJ	−0.11%	3.90%	−0.13%	0.27%	−0.22%	−1.19%	−2.50%
RN	−1.51%	0.99%	−0.56%	−1.34%	−1.32%	−0.02%	1.61%
RO	8.16%	4.02%	0.16%	1.48%	−1.61%	−0.02%	3.13%
RR	−1.67%	1.14%	0.18%	−1.13%	0.79%	−0.59%	−1.82%
RS	3.00%	4.04%	0.04%	0.29%	−2.00%	−0.25%	0.76%
SC	1.05%	4.10%	0.09%	0.55%	−2.70%	−0.64%	−0.40%
SE	1.36%	1.47%	−0.07%	−0.23%	−1.69%	−0.11%	2.09%
SP	1.94%	3.91%	−0.22%	−0.10%	0.49%	−0.74%	−1.56%
TO	9.34%	3.50%	−0.03%	1.47%	0.00%	0.33%	3.05%
Arithmetic average	1.96%	2.62%	−0.05%	0.07%	−0.75%	−0.44%	0.33%

Abbreviations: OPEI, output-oriented production environment index; SNI, statistical noise index; TI, technology index; TFPI, total factor productivity index.

Leite-Filho et al. (2021) investigated the relationship between historical deforestation and rainfall across the Southern Brazilian Amazon (SBA) and found that higher deforestation reduces rainfall. Their main results suggest that, under what they define as a weak governance scenario, SBA may lose 56% of its forests by 2050, while reducing deforestation could prevent US$ 1 billion of agricultural losses in SBA annually. Marengo et al. (2018) described how the Amazon rainforest affects the rainfall and temperature in the Centre-West, Southeast and South regions, because of its impact on hydrology, climate and carbon cycling. They argued that Amazon deforestation reduced rainfall in Amazon forests, which negatively affects regional hydrology, resulting in the rising vulnerability of ecosystem services for the population within and beyond the Amazon region. Deforestation thus leads to rainfall reduction and rising temperatures in the states with higher agricultural productivity.

4 | CONCLUDING REMARKS

This article examined Brazilian agricultural TFP growth from 1995 to 2017, using panel data from 510 Brazilian micro-regions in combination with climate data and a land suitability index to estimate production technology through stochastic production frontier methods. Our main results are consistent with previous analyses of Brazilian agricultural productivity and demonstrated that higher TFP growth occurred in the production frontier areas.

We provide a better understanding of recent Brazilian agricultural TFP growth, because our findings indicate that technological progress and production environment are the main determinants driving TFP at the state level. We also found that rising temperatures have negative effects on agricultural production, while the estimated impact of precipitation is positive. These findings are critical to developing effective sectoral and regional policies to mitigate changes in climatic conditions in terms of productivity and income, especially in states with an intensive focus on agricultural production. We then calculated that Brazilian agriculture TFP increased by 1.96% per annum between 1995 and 2017; the driving force was technological progress, which increased by 2.62% per annum, while the environmental index decreased by 0.75% per annum, and the production environment increased by 0.07% per annum.

It is essential to promote public and private investments in technological innovations and infrastructure to keep the relatively higher levels of technological progress observed across the Brazilian states—as well as the development of environmentally sustainable practices and resilient seeds, for example—to reduce negative climate impacts estimated. Public policies designed to improve farmers' access to technical assistance might raise the technical efficiency levels of the micro-regions. Further research might identify policy and investment strategies at the regional level and, more specifically, those directed at promoting sustainable environmental agricultural growth (land-saving technology) and developing technological innovation under potential changes in climate conditions.

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DATA AVAILABILITY STATEMENT

Data will be made available on request.

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SUPPORTING INFORMATION

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