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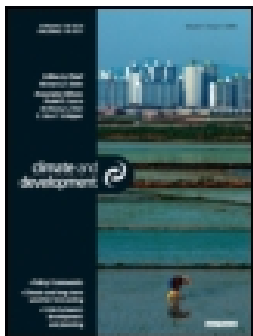
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# Climate resilience programmes and technical efficiency: evidence from the smallholder dairy farmers in the Brazilian semi-arid region

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## ABSTRACT

This paper evaluates the technical efficiency of smallholder dairy farmers assisted by a climate resilience programme in the Brazilian semi-arid region. We use stochastic frontier models applied to a panel with quarterly data for 43 dairy family farmers assisted by the MAIS programme (*Módulo Agroclimático Inteligente e Sustentável*) between January 2016 and March 2018. Results highlight how the assistance to implement climate-smart production practices, in addition to access to basic technologies, played a key role in improving the frontier of production of dairy farmers. We also show that increasing temperature continues to be the main threat to the continuous growth of technical efficiency in the region. Our findings provide insights for policy and decision-makers in designing adaptive strategies to reduce the vulnerability of impoverished family farmers that face extreme weather events.

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## KEYWORDS

Technical efficiency; climate resilience; dairy farms; semi-arid regions; climate-smart agriculture; stochastic frontier models

## 1. Introduction

Family farmers in the semi-arid region of Brazil are extremely vulnerable to climate change. This scenario is explained by various factors such as advanced desertification, land degradation, rainfall deficits, water scarcity, and precarious socio-economic and infrastructure conditions (Burney et al., 2014). Droughts have intensified in the Brazilian semi-arid region since the 1990s and have become more widespread since the 2010s (Alvalá et al., 2019; Costa et al., 2020; Marengo et al., 2018). Besides, climate forecasts indicate worsening conditions related to rainfall deficits and soil aridity in this region during the second half of the twenty-first century (IPCC, 2014).

Several studies have investigated the impact of climate change on agricultural production in different regions of the world (Donatti et al., 2019; Hannah et al., 2017; Key & Sneeringer, 2014; Mendelsohn & Dinar, 2009; Omerkhil et al., 2020; Pires et al., 2016). More recently, studies have focused on how adaptive strategies may offset the negative impacts of climate change on production and food security (de Sousa et al., 2018; Di Falco et al., 2011; Jamshidi et al., 2020; Oumer, 2019; Salat & Swallow, 2018; Smit & Wandel, 2006; Teklewold et al., 2019; Teklewold et al., 2019; Tong et al., 2019). A general concern is that adaptation may require investment in technologies and production practices that are not affordable for smallholder family farmers in less developed regions.

However, specific experiences have shown that adopting basic management practices may bring remarkable economic gains to family farmers facing yield-limiting factors (Adego et al., 2019; Onyeneke, 2020; Shahzad & Abdulai, 2020). In this context, climate resilience programmes have been formulated to help counteract the effects of climate change on

vulnerable rural areas in the developing world. For example, Khanal et al. (2018) show evidence that climate change adaptive strategies (CCAS), designed by different programmes in Nepal, had a positive impact on the average yield and technical efficiency of smallholder farmers. Using the stochastic frontier (SF) model, the authors also indicated that socioeconomic characteristics (such as education and market access) played an essential role in explaining farmers' efficiency. Khanal et al. (2021) also showed that Nepalese farmers that adopted CCAS were, on average, 11% more efficient than non-adopters. Ankras Twumasi and Jiang (2021) evaluated the impact of CCAS on the technical efficiency of goat farmers in Ghana, showing that these practices helped increase farmers' efficiency. Using SF models, Bai et al. (2019) indicated that CCAS improved livestock production's technical efficiency among vulnerable Chinese farmers. Ojo and Baiyegunhi (2020) conducted a similar analysis among smallholder rice farmers in Nigeria, pointing to the importance of CCAS in enhancing average rice yield and technical efficiency.

The purpose of this study is to evaluate the technical efficiency of family dairy farmers assisted by a climate resilience programme in the Brazilian semi-arid region. The programme is called MAIS, *Módulo Agroclimático Inteligente e Sustentável*, which means Sustainable Smart Agro-climatic Module. In 2016, the MAIS programme implemented an approach for enabling smallholders to sustainably achieve yield and economic gains through improvements in management practices and the use of locally-adapted and low-cost technologies. Therefore, our analysis's central purpose is to identify if and how family farmers can maximize their feasible production given only a bundle of limited but strategically

selected inputs and technologies. We also evaluated how the main exogenous shocks in the region, weather conditions, may compromise farmers' technical efficiency.

This study provides insights regarding climate-smart practices and their impacts among smallholder farmers. Results from this research can be particularly helpful for policy- and decision-makers in formulating and designing effective adaptive strategies to reduce vulnerability and improve the resilience of impoverished family farmers that face extreme weather events and climate change.

## 2. Background

The study focuses on the Jacuípe basin area (JBA), located in the state of Bahia – Northeast region of Brazil (Figure 1). The JBA is part of the most populous semi-arid area in the world (the Brazilian *Sertão*<sup>1</sup>), covering 10,739 km<sup>2</sup> (14 municipalities) with a population of 238,127 people in 2018. The region is plagued by high poverty levels, inequality, and food insecurity (Gori Maia et al., 2018).<sup>2</sup> The main agricultural activities in the region are extensive livestock and dairy farming. According to the 2017 Agricultural Census, nearly 26,000 smallholder farmers lived in the JBA, and one-third of them are dairy farmers.<sup>3</sup>

Analyzing the climate conditions, the area has been severely hit by increasing temperatures and recurrent droughts. Between 1961 and 2018, the average monthly temperature increased by 0.4°C per decade, reaching a minimum (maximum) average of 21°C (31°C) in the 2010s (Figure 2). The region has also historically suffered prolonged and irregular periods of drought, which seems to have worsened in the last decades: the average rainfall has reduced by 10 mm per decade since the 1960s.

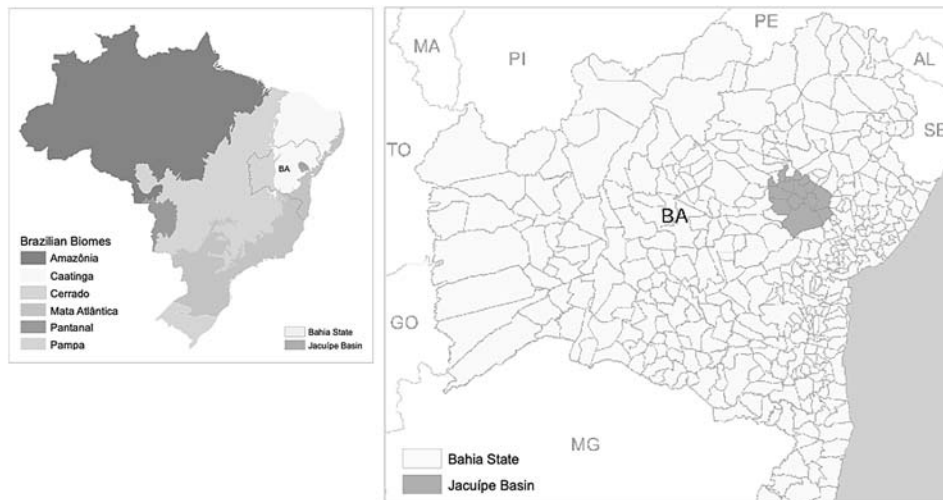
In this context, a multi-stakeholder group called *Adapta Sertão* created the MAIS programme in 2014. The programme's objective was to enhance the productivity and efficiency of smallholder livestock and dairy family farmers, using climate change adaptative strategies through the adoption of low-cost technologies and production practices, along

with market integration strategies. In addition to aiming to achieve food security, the programme sought to reduce the environmental impact of agricultural activities. The programme was financed by the Interamerican Development Bank (IDB) and Nordic Development Bank (NDF), with a minor contribution from the Bahia State Government.

Between 2016 and 2018, the MAIS programme assisted 100 family farmers<sup>4</sup> in their milk and sheepmeat production. The selection of the MAIS farmers was partially random. The *Adapta Sertão* applied a survey in the JBA in 2015 and ranked the family farmers using a score containing seven main dimensions: education, family structure, technical training, financial resources, market integration, access to water, land area, and management. Fifty farmers were strategically (non-randomly) selected among those with the best scores. The selection of the other 50 farmers was based on: (i) a random selection of those farmers who met threshold criteria determined by *Adapta Sertão* but who were not among the *Adapta* selection; (ii) farmers recommended by the local cooperative and rural associations.

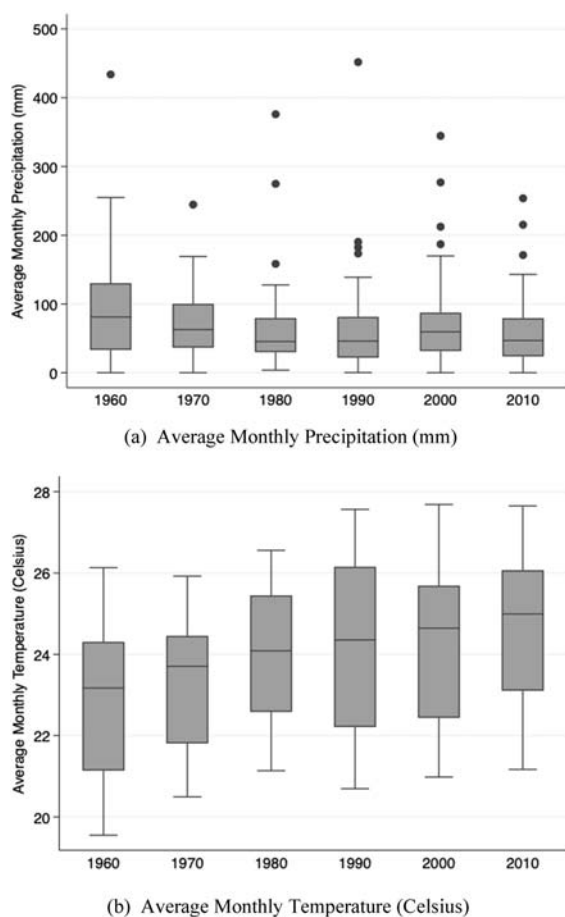
The programme consisted of four interrelated steps: adoption of improved production practices ("modules"), technical training, financial orientation, and monitoring and evaluation (Voigtlaender et al., 2017). The production modules required a minimum area of 20 hectares and included a package of 20 locally adapted practices and technologies. The minimum area of production was established to guarantee: (i) a sustainable provision of pastures, area for Livestock-Forest-Pasture integration, area for hay production and forage, mainly *Opuntia-Ficus Indica* (a cactus)<sup>5</sup>; (ii) a maximum number of heads per module to guarantee a sustainable production in the long run without the depletion of natural resources; (iii) best animal management practices; (iv) construction of wells, water cisterns, and earth dams to ensure family and animal water needs during prolonged droughts; recommendation of small-scale and low-cost machinery.

The MAIS programme may improve farmer's efficiency primarily through the access to technical guidance, which is still scarce in the region (Gori Maia et al., 2018). The quality and duration of the technical assistance were one of the greatest



**Figure 1.** Municipalities in the Jacuípe basin area (JBA). Note: the municipalities in the JBA are Baixa Grande, Capela do Alto Alegre, Gavião, Ipirá, Mairi, Nova Fátima, Pé de Serra, Pintadas, Quixabeira, Riachão do Jacuípe, São José do Jacuípe, Serra Preta, Várzea da Roça, and Várzea do Poço.

strengths of the MAIS programme. The farmers were uniformly assisted by professional technical assistance for two to three years through monthly four-hour visits to properly implement and manage production in the new system. In addition to organizing and planning the activity, the experts provided support and information on water and food storage, rotation and pasture recovery, mechanization, animals' management, among other extension services. In other words, the programme taught farmers how to better use the resources they had available. For example, one primary strategy disseminated in the programme was how to accordingly cultivate densely spaced *Opuntia* cactus, which can be used to feed the herd during periods of prolonged drought. The programme also included a financial orientation plan to implement the modules and advised farmers in four areas: (i) selling of unused assets; (ii) investment of farmers' savings; (iii) access to government incentives/subsidies to agriculture; (iv) access to credit programmes. Finally, each farm was monitored and evaluated by collecting quantitative and qualitative technical, economic, environmental, and production data. We used this data to analyze the technical efficiency of MAIS farmers.



**Figure 2.** Distribution of average monthly values of precipitation (mm) and temperature (oC) in each decade, JBA between the 1960s and the 2010s. (a) Average Monthly Precipitation (mm). (b) Average Monthly Temperature (Celsius). Note: Monthly values from the meteorological station located in the Serrinha municipality, the closest from the JBA (nearly 30 miles of distance). Average values represent the mean of the monthly values observed in each decade (1960-1969, 1970-1979, 1980-1989, 1990-1999, 2000-2009, 2010-2017). Source: INMET (2017)

Previous studies analyzed how the MAIS programme strengthened the adaptive capacity of family farmers in the Brazilian semi-arid region. Simoes et al. (2010), for example, described how the project helped family farmers to implement adaptive strategies in the municipality of Pintadas in the JBA. Gori Maia et al. (2019) indicated that the programme had substantive and significant impacts on production practices, land management, and quality of life in general. Our study contributes to this debate, exploring the technical efficiency of the family dairy farmers assisted by the MAIS programme. Local experiences could provide insights to improve adaptation policy frameworks for climate change aiming to reduce small-holder farmers' vulnerability and alleviate poverty.

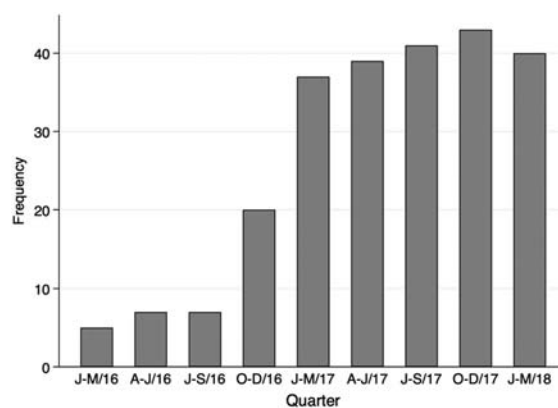
### 3. Material and methods

#### 3.1. Data source

We use a panel with monthly (longitudinal) data for 43 dairy farmers assisted by the MAIS programme between January 2016 and March 2018. The information was collected by four technicians trained by the MAIS programme. The same technician visited each farm every month to collect data for monitoring, provide technical assistance, and production planning. An agronomist and a technical director specialized in milk production supervised the visits, reducing potential measurement errors in the data collection. To reduce volatility and missing data (attrition), we computed farmers' monthly average production and inputs in each quarter. Missing data may arise predominantly because the small-scale production in the region is based on scarce resources and subjected to extreme irregularities.

The programme began with only seven farmers in the first three quarters of 2016 and reached a peak in the first quarter of 2017, with 43 farmers (Figure 3). Our final sample comprises an unbalanced panel data with 239 observations, distributed in 9 time periods (quarters).

Our outcome of interest is the average milk production (*milk*, in litres).<sup>6</sup> The main predictor of interest is the cumulative number of quarters each farmer was assisted by the programme (*quarters*), a proxy for the MAIS programme's learning gains. In other words, we assume that the cumulative



**Figure 3.** Total number of farmers per quarter between 2016 and 2018. Note: January to March (J-M), April to June (A-J), July to September (J-S), October to December (O-D). Source: Survey data

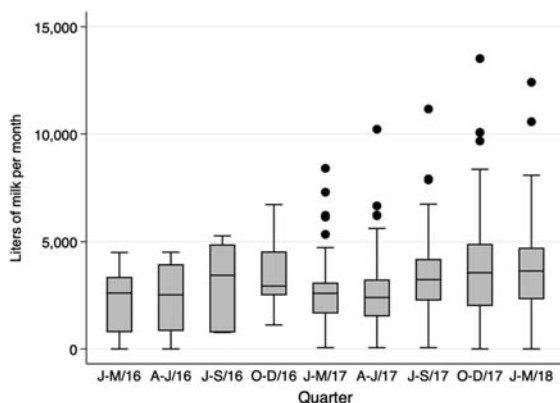


number of quarters in the programme may capture the net effect of MAIS's technical assistance on milk production once we control for the primary inputs of production. The inputs of production available in our panel data are a) *size*, farm size in hectares; b) *labor*, hours of hired labour (temporary or permanent)<sup>7</sup>; c) *investment*, a binary variable that assumes 1 when the total investment since entering in the programme was greater than zero, i.e. the variable captures the cumulative investment until the quarter.

We also obtained information for each farm's infrastructure and access to technology: a) *cistern*, a binary variable that equals 1 for the presence of water cistern in the farm with a minimum storage capacity of 50,000 litres; b) *tractor*, a binary variable that equals 1 for the presence of (2 or 4 wheels) tractor in the farm; c) *cooling*, a binary variable that equals 1 for the presence of milk cooling system. These three variables are time-invariant because they were collected in an independent survey applied at the end of the programme (1st quarter of 2018). These time-invariant regressors are available for 37 of 43 farmers who participated in the survey.

Figure 4 shows the distribution of the average production of milk per month between quarters 1 and 9. We identify a structural break between the 4th and the 5th quarters when 30 new farmers entered the MAIS programme. Between the 5th and the 9th quarter, the median milk production increased by 40% (from 2,593 to 3,635 litres of milk per month). Notably, a few outliers reached more than 10,000 litres per month, suggesting that they may be in the frontier of production and that it may still be possible to improve technical efficiency.

The MAIS farmers show to be positively selected in terms of land size, but they use few inputs in the production, and access to essential technologies is scarce. The average farm size was 42.2 hectares (Table 1), 50% higher than the region's average. Nonetheless, these farmers showed low investment capacity: only 37.2% of them invested in the period. Nearly three-quarters of the dairy farmers hired labour (temporary or permanent), while the other quarter relied exclusively on family labour – the average hours per month of hired labour is 394.7. The technology adoption in the production system



**Figure 4.** Distribution of monthly production of milk (liters), by quarter, for all MAIS farmers between 2016 and 2018. Note: January to March (J-M), April to June (A-J), July to September (J-S), October to December (O-D). Source: Survey data.

was limited. While around one-third of the farmers had a milk cooling system, only 15.2% had a tractor. Furthermore, only 24.8% of the farmers had a water source to ensure family and animal needs during prolonged droughts. Finally, the average period of participation in the MAIS programme was 3.5 quarters.

We also analyzed the impact of climatic data on technical efficiency. Our data came from conventional weather stations of the National Meteorological Institute (INMET). We initially interpolated the stations' data through all municipalities using the method of Inverse Distance Weighting (IDW) (Kurtzman & Kadmon, 1999). The IDW method makes a weighted linear combination of all meteorological stations' data. Weights are proportional to the inverse of the distances: the larger the distance, the lower the weight. Although the interpolation considered a sample of 261 weather stations in Brazil, the interpolated values used in our analysis were strongly influenced by those stations located close to the JBA.

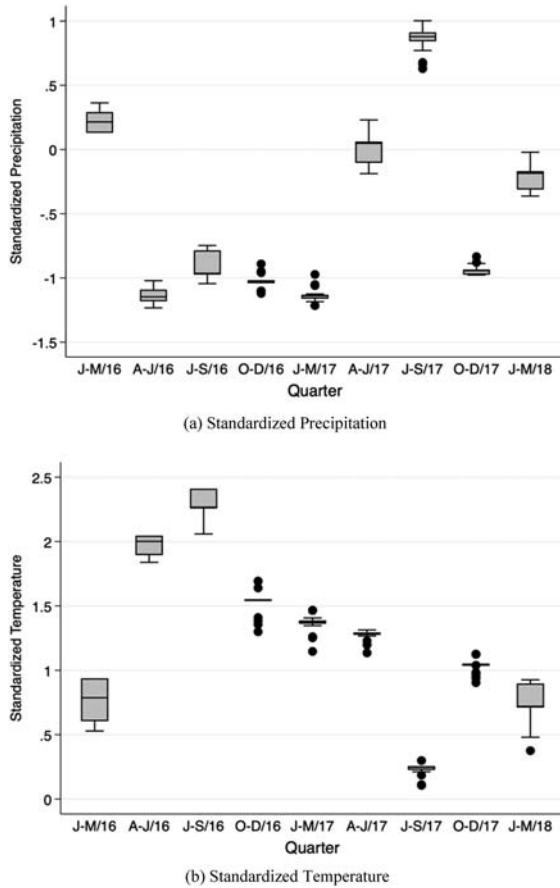
Using the interpolated data, we then estimated two indicators of short-term climate shocks in the farm's municipality: average monthly standardized temperature ( $Z - temperature$ ) and total monthly standardized precipitation ( $Z - precipitation$ ). The standardized measures are given by [(monthly value – historical monthly average between 1961 and 2018)]/standard deviation]. The standardized measures eliminate potential historical climate differences in the region and provide an intuitive interpretation for the climate variables: positive values mean temperature or precipitation above the historical average and negative values mean monthly averages below the historical average (Dell et al., 2014).

Figure 5 shows the distribution of  $Z - temperature$  and  $Z - precipitation$  between the 1st quarter of 2016 and the 1st quarter of 2018. The family farmers have faced harsh climate conditions during the implementation of the MAIS program. The temperature was above the historical average (positive values of  $Z - temperature$ ) in the whole period of analysis. The precipitation was below the historical average (negative

**Table 1.** Descriptive statistics. Sampled farmers between the 1st quarter of 2016 and the 1st quarter of 2018.

Variables	Description	Farmers	Average	Std. Dev.
<i>Milk</i>	Litres of milk per month	43	3,392	2,277
<i>Size</i>	Farm size in hectares	43	42.200	28.500
<i>Labour</i>	Monthly hours of hired farm labour divided per 100	43	3.947	4.583
<i>Investment</i>	1 when the total investment since entering in the programme is greater than zero, 0 otherwise	43	0.372	0.484
<i>Cistern</i>	1 for the use of water cistern with a minimum storage capacity of 50,000 litres, 0 otherwise	37	0.248	0.433
<i>Tractor</i>	1 for the use of a tractor, 0 otherwise	37	0.152	0.360
<i>Cooling</i>	1 for the use of milk cooling system, 0 otherwise	37	0.343	0.476
<i>Quarters</i>	Total number of quarters in the programme	43	3.548	2.000

Note: The data were obtained at the farmer level through interviews carried out by the technicians of the MAIS programme. Farmers refer to the number of farmers with non-missing values for each variable. The averages represent the mean of monthly values for all farmers and quarters between January 2016 and March 2018. Source: survey data



**Figure 5.** Distribution of average values of standardized precipitation and standardized temperature. Sampled farmers between the 1st quarter of 2016 and the 1st quarter of 2018. (a) Standardized Precipitation. (b) Standardized Temperature. Note: January to March (J-M), April to June (A-J), July to September (J-S), October to December (O-D). Source: INMET (2017)

values of  $Z - precipitation$ ) in 6 of 9 quarters of analysis. We also observed large variations between quarters and across farmers (within quarters). For example, the  $Z - temperature$  ranged from a minimum of 0.1 standard deviation in the 3rd quarter of 2017 to a maximum of 2.4 standard deviations in the 3rd quarter of 2016. Standardized precipitation ranged from  $-1.23$  standard deviations in the 2nd quarter of 2016– $1.00$  standard deviation in the 3rd quarter of 2017. In the 2nd quarter of 2017, the  $Z - precipitation$  across farmers ranged from a minimum of  $-0.19$  standard deviation to a maximum of  $0.23$  standard deviations.

### 3.2. Empirical strategy

We used SF models to analyze the technical efficiency of MAIS farmers. The SF models allowed us to (i) evaluate how close the farmers were to maximum production efficiency and (ii) identify how technical inefficiency may be affected by climatic conditions. SF models were initially developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) to estimate the inefficiency associated with a traditional production function.

The first step of our empirical strategy consisted of defining a function for the average milk production (production function). When  $y_{it}$  is the production (*milk*) of the farm  $i$  in quarter

$t$  and  $x_{it}$  a vector of  $k$  explanatory factors (inputs of production), the production function for panel data is given by:

$$\ln y_{it} = x_{it}\beta + \delta t + c_i + e_{it} \quad i = 1, \dots, n \quad (1)$$

The coefficient  $\delta$  measures the farmers' average learning gains, i.e. the improvements in farmers' production per quarter in the MAIS programme (variable  $t$ ). Our matrix  $x$  includes both time-varying (*ln size*, *labor*, and *investment*) and time-invariant variables (*cistern*, *tractor*, and *cooling*). Panel data models strength causal inference because it controls omitted farmers' characteristics that are constant over time (such as prior technological knowledge, agricultural skills, social and human capital).

The component  $c_i$  is the time-invariant unobservable farmer heterogeneity (for example, prior level of climate vulnerability and agricultural skills), which can be controlled by random or fixed effects (Greene, 2005). The random-effects estimator is more efficient than the fixed effects estimator, but it can be biased if the unobservable heterogeneity  $c_i$  is correlated to explanatory variables ( $t$  and  $x_{it}$ ). In turn, one main limitation of the fixed effects estimator is that it does not accept time-invariant regressors, which is the case of some of our inputs of production (*cistern*, *tractor*, and *cooling*). We used the Hausman test to compare the random and fixed effects and check the consistency of random-effects estimates (Hausman, 1978).

The second step of our strategy is based on an SF model. The SF model allows us to disaggregate the error  $e_{it}$  into two specific components: i) random shocks ( $v_{it}$ ), resultant, for example, from unexpected or unobserved factors (for example, animal disease); ii) components associated with technical inefficiency ( $u_{it}$ ), (for example, difficulty in farmers' knowledge uptake and environmental conditions). In other words:

$$\ln y_{it} = x_{it}\beta + \delta t + c_i + v_{it} - u_{it} \quad (2)$$

The shock  $v_{it}$  is assumed to be independent of  $u_{it}$  and identically distributed. The component  $u_{it}$  is positive and represents technical inefficiency. In other words,  $u_{it}$  represents a decrease in the maximum feasible production. The component  $u_{it}$  can also be represented by a function of a vector  $z_{it}$  of characteristics that are beyond the farmers' control (Battese & Coelli, 1995). In other words, we have:

$$u_{it} \sim N^+(\mu_{it}, \sigma_u^2) \quad (3)$$

$$\mu_{it} = z_{it}\varnothing \quad (4)$$

In this case,  $u_{it}$  has a normal positive distribution with an average value  $\mu_{it}$  conditional to the characteristics  $z_{it}$ , and  $\varnothing$  is its vector of coefficients. The vector  $z_{it}$  may represent observable and unobservable factors, such as household, farm, institutional, and regional characteristics. We are particularly interested in the impacts of climate shocks on technical inefficiency, and our vector  $z_{it}$  includes two variables:  $Z - temperature$  and  $Z - precipitation$  in the farm's  $i$  municipality at quarter  $t$ .

The SF model can be estimated in one- or two-steps (Wang & Schmidt, 2002). The one-step approach fits both equations (2) and (4) simultaneously. The two-step approach fits firstly equation (2) and secondly equation (4) using the first-stage residuals. We used the one-step approach since it is consistent,

while the two-stage approach may be biased (Wang & Schmidt, 2002). The estimation strategy consists of maximizing the function of log-likelihood conditioned to the vector of coefficients  $\beta$  and  $\theta$ , and to the parameters  $\sigma^2 = \sigma_v^2 + \sigma_u^2$  and  $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$ , where  $\sigma_v^2$  is the variance of  $v$  (Battese & Coelli, 1995).

A particularly useful analysis in the SF model is the estimation of technical efficiency. Based on equation (2), the production  $y_{it}$  can be given by the product of three components:

$$y_{it} = \exp(x_{it}\beta + \delta t + c_i) \times \exp(v_{it}) \times \exp(-u_{it}) \quad (5)$$

The product of the first two components defines the production possibility frontier, i.e. the production level considering a total productive efficiency hypothesis. In turn, the inefficiency component  $\exp(-u_{it})$  represents the distance to the production frontier resulting from inefficiency. Based on this analysis, we can extract one of the most common technical efficiency measures (Coelli et al., 1998):

$$TE_{it} = \frac{y_{it}}{\exp(x_{it}\beta + \delta t + c_i) \times \exp(v_{it})} = \exp(-u_{it}) \quad (6)$$

$TE_{it}$  assumes a value between 0 and 1 and represents the ratio between the observed production for  $i$  and its maximum expected production. In other words,  $TE_{it}$  represents the share of the maximum production attained by  $i$  in the quarter  $t$ . Thus, the closer  $TE_{it}$  is to 1, in both situations, the closer  $i$  is to total efficiency at time  $t$ .

## 4. Results and discussion

### 4.1. Production function models

We first estimate equation 1 to better define the production function specification and estimation strategy. Table 2 reports random effect estimates for coefficients of the model for the average log of *milk* as a function of the number of *quarters* that family farmers are in the programme (equation 1). We tested three different (nested) specifications (Models 1-3). Model 1 is based on a traditional Cobb–Douglas production function: the average log of production as a linear function of the log of area (*ln size*), hours of hired labour (*labor*), and a binary for investment (*investment*).<sup>8</sup> Model 2 is based on a translog production function: the average log of production as a function of the inputs (*ln size*, *labor*, and *investment*), the square of the continuous variables (*ln size* and *labor*), and the interactions between the inputs (*ln size*  $\times$  *labor*, *ln size*  $\times$  *investment*, and *labor*  $\times$  *investment*). Model 3 adds controls for time-invariant technological variables (*cistern*, *tractor*, and *cooling*) and all interactions with these variables. Since time-invariant technological variables are only available to a subset of farmers, we missed 29 observations in Model 3. The estimates for Models 2 and 3 in Table 2 refer to each variable's main effect ( $\partial Y / \partial X$ ) at the means, i.e. fixing all other variables at their means.

The Hausman test's null hypothesis in Table 2 is that the random effect estimates are consistent and more efficient than the fixed effect estimates. The Hausman tests for Models 1 and 2 indicate that the differences between fixed and random effect estimates are insignificant, i.e. the random effect method

**Table 2.** Random effect estimates for the dependent variable log of monthly average of milk production.

Variable	Model 1	Model 2 <sup>a</sup>	Model 3 <sup>a</sup>
<i>Quarters</i>	0.106 *** (0.014)	0.110 *** (0.016)	0.098 *** (0.014)
<i>ln size</i>	0.102 (0.086)	0.107 (0.111)	0.376 * (0.171)
<i>Labour</i>	0.035 * (0.017)	0.068 * (0.033)	0.032 ** (0.010)
<i>Investment</i>	-0.071 (0.075)	-0.124 (0.076)	-0.064 (0.071)
<i>Cistern</i>			0.262 (0.148)
<i>Tractor</i>			-0.073 (0.173)
<i>Cooling</i>			0.348 * (0.139)
<i>n</i>	235	235	206
<i>R</i> <sup>2</sup> -within	0.320	0.366	0.414
Hausman ( $\chi^2$ ) <sup>b</sup>	8.70	5.53	-
Selection ( <i>t</i> ) <sup>c</sup>	-1.79	-2.12 *	-1.15

Sampled farmers between the 1st quarter of 2016 and the 1st quarter of 2018. Notes: \*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ . Robust standard errors in parentheses.

Model 1 is a linear function of the independent variables (Cobb–Douglas function). Model 2 and 3 are functions of the independent variables and their interactions (Translog function). Estimates for Model 2 and 3 refer to the main effect of each variable at the means of covariates. <sup>b</sup>The null hypothesis in the Hausman specification test is that the fixed effect estimates are equal to the random effect estimates for model 1, i.e. the random effect estimates are consistent and more efficient. The chi-square statistic used in the Hausman test presents four degrees of freedom in Model 1 and eight degrees of freedom in Model 2. <sup>c</sup>The null hypothesis in the sample selection test is that sample selection is uncorrelated with the idiosyncratic errors, i.e. the estimates without sample selection correction are consistent.

provides consistent and the most efficient estimates. The Hausman test does not apply to Model 3 because it includes time-invariant regressors and can only be fitted using a random effect estimator. Nonetheless, the random-effects estimates' consistency may also hold in Model 3 because it is an extension of Models 1 and 2 (nested models).<sup>9</sup>

Table 2 also shows the results of the sample selection test proposed by Verbeek and Nijman (1992). The null hypothesis assumes that the unobservable selectivity is unrelated to the idiosyncratic errors, i.e. the estimates are robust to selectivity. We have moderate evidence of sample selection ( $p < 0.05$ ) only in Model 2. Model 3 is robust to selectivity and presents the best statistics of the goodness of fit. The  $R^2$  equals 41.4% against 32% in Model 1 and 36.6% in Model 2. Model 3 will henceforth be the focus of our analysis.

The estimates for the net impacts of the number of quarters in the MAIS programme (*quarters*) are significant and robust in all model specifications. Results indicated that the time in the MAIS programme had a positive impact on dairy farming: average milk production increased by nearly 10% (Model 3) for each quarter of technical assistance provided by the MAIS programme. These results follow the literature on the importance of agricultural extension services to transfer technology to smallholder farmers (Khonje et al., 2018; Shahzad & Abdulai, 2020; Wainaina et al., 2018; Zhang et al., 2016).

### 4.2. Stochastic frontier models

Once we have defined the best model specification (Model 3) and estimation strategy (random effects) in section 4.1, we



now analyze SF models for milk production (equations 2 and 4). Table 3 shows the estimates for the SF models considering two different specifications: Model 3-A is based on equation 2, assuming that the frontier of milk production is a translog function of the time in the programme (*quarters*) and the inputs of production (*ln size*, *labor*, *investment*, *cistern*, *tractor*, and *cooling*); Model 3-B is based on equations 2 and 4, assuming that the frontier of milk production is simultaneously defined by a translog function for the log of milk production (equation 2) and a function for the mean technical inefficiency (equation 4). Climate shocks ( $Z - \text{Temperature}$  and  $Z - \text{Precipitation}$ ) are the regressors ( $z$ ) in the model for the mean technical inefficiency (equation 4).

The SF models fitted well to our data: the variance of the disturbances associated with random shocks ( $\sigma_v^2$ ) and technical inefficiency ( $\sigma_u^2$ ) are statistically different from zero in both models. The variability of the technical inefficiency is between 12% ( $\lambda$  in Model 3-B) and 27% (Model 3-A) higher than that of the random shocks, suggesting that inefficiency plays a crucial role in explaining farmers' differences in milk production.

The estimates indicate that the duration of the technical assistance provided by the MAIS programme increased the frontier of milk production between 6.4% ( $e^{0.062} - 1 = 0.064$  in Model 3-B) and 7.7% ( $e^{0.074} - 1 = 0.077$  in Model 3-A) per quarter. Additionally, basic inputs of production also played a key role in improving the frontier of production. Every 100 additional hours of hired non-family labour in the month increased production's frontier by nearly 7% ( $e^{0.063} - 1 = 0.065$  in Model 3-A and  $e^{0.065} - 1 = 0.068$  in Model 3-B). Making investments in production increased the frontier by nearly 18% ( $e^{0.163} - 1 = 0.177$  in Model 3-A and

$e^{0.173} - 1 = 0.189$  in Model 3-B). Findings also highlighted that access to milk cooling system is the most strategic technology to increase the production's frontier: the use of a cooling system increased the frontier by nearly 29% ( $e^{0.255} - 1 = 0.291$  in Model 3-A and  $e^{0.250} - 1 = 0.283$  in Model 3-B). This result is in line with recent studies (Bai et al., 2019; Khanal et al., 2018; Ojo & Baiyegunhi, 2020), which used the SF approach and showed a positive impact of climate-smart practices on technical efficiency.

Model 3-B also indicates that increasing temperature may be a major concern in milk production's technical efficiency. For each increase of one standard deviation in the average monthly temperature, technical inefficiency increases by 0.282 point. This result means that milk production would be 32.6% ( $e^{0.282} - 1 = 0.326$ ) lower than in the frontier of production. This is a crucial aspect once, in some quarters of the analyzed period, the average temperature was two standard deviations larger than the historical average. The impacts of precipitation on technical inefficiency is also positive and significant at 5%: for each increase of one standard deviation in total monthly precipitation, technical inefficiency increases by 19.8% ( $e^{0.180} - 1 = 0.198$ ). Qi et al. (2015) also identified that marginal increases in precipitation might negatively impact dairy farm productivity. However, our results reflect mainly short-term impacts of temperature and precipitation. A longer-term analysis would be necessary to understand better climate resilience in an area with many timescales of drought.

Appendix A shows the SF estimates (Models 3-A and 3-B) with binaries for calendar quarters. The idea is to check the robustness of our estimates to seasonality. The estimates of Appendix A for the time in the programme (*quarters*) and inputs of production are quite similar to those from Table 3. The main difference is the insignificance of the estimates for the inefficiency component (variables  $Z - \text{temperature}$  and  $Z - \text{precipitation}$ ). Multicollinearity helps explain this result because weather shocks varied by season in the JBA. Shocks of high temperature were more frequent in the autumn (average  $Z - \text{temperature}$  was 1.40 in the second quarter and 1.05 in the whole period), and; shocks of low precipitation were more frequent in the spring (average  $Z - \text{precipitation}$  was equal to  $-0.97$  in the fourth quarter against  $-0.37$  in the whole period).

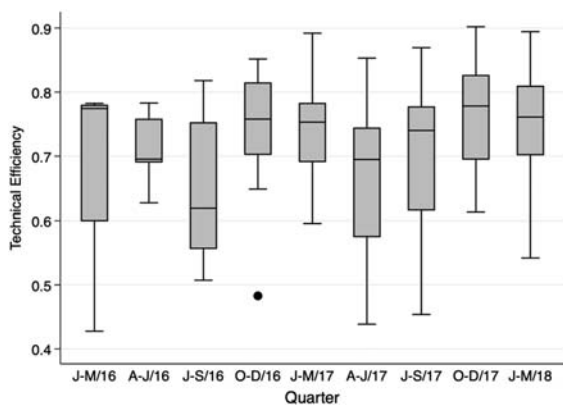
Advanced desertification, land degradation, rainfall deficits, water scarcity, and precarious socioeconomic and infrastructure conditions have historically affected smallholder farmers' productivity in the JBA. Burney et al. (2014) attributed the reduced productivity to farmers' lack of climate resiliency and their dependence on scarce water resources in the region. Nonetheless, our results indicate that the time in the MAIS programme had an essential effect on milk production. In general, as Zhang et al. (2016) argued, it is possible to propose affordable adaptive strategies that are efficient and easily assimilated by small producers. Particularly considering the MAIS programme, locally adapted and low-cost technologies, such as a milk cooling system, have remarkably improved farmers' production gains.

Figure 6 shows the estimates for the farmers' technical efficiency ( $TE$  in Equation 6) using Model 3-B. We focus our analysis between the fifth (January-March 2017) and the

**Table 3.** Frontier model results for log of milk production.

	Model 3-A	Model 3-B
	Frontier of production (ln <i>milk</i> )	
<i>Quarters</i>	0.074 *** (0.016)	0.062 *** (0.018)
<i>ln size</i>	0.198 (0.146)	0.182 (0.140)
<i>Labour</i>	0.063*** (0.012)	0.065*** (0.012)
<i>Investment</i>	0.163* (0.074)	0.173* (0.075)
<i>Cistern</i>	0.098 (0.107)	0.080 (0.105)
<i>Tractor</i>	0.083 (0.115)	0.078 (0.114)
<i>Cooling</i>	0.255** (0.089)	0.250** (0.088)
	Technical inefficiency ( $\mu$ )	
$Z - \text{Temperature}$		0.282* (0.122)
$Z - \text{Precipitation}$		0.180* (0.089)
$n$	206	206
$\sigma_u$	0.381*	0.324*
$\sigma_v$	0.301***	0.288***
$\lambda = \sigma_u / \sigma_v$	1.269***	1.125***
Log likelihood	-91.3	-89.5

Sampled farmers between the 1st quarter of 2016 and the 1st quarter of 2018. Notes: \*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$ . Standard errors in parentheses.  $\sigma_u$  is the standard deviation of the component associated with the technological inefficiency and  $\sigma_v$  is the standard deviation of the idiosyncratic error. Estimates for the frontier of production refer to the main effect of each variable at the means of covariates.



**Figure 6.** Distribution of the estimates of the technical inefficiency in the milk production, Model 3-B. aNote: January to March (J-M), April to June (A-J), July to September (J-S), October to December (O-D). Source: Survey data

ninth (January-March 2018) quarters when most farmers participated in the MAIS programme. One main achievement of the programme in this period was to increase the top performers' technical efficiency, since the third quartile increased from 0.743 to 0.783 (4 percentage points). The median TE increased by two percentage points (from 0.704 to 0.723), and the mean TE increased by 2.4 percentage points (from 0.696 to 0.721). The mean TE in the whole period increased from 65% in the first quarter (January-March 2016) to 72% in the ninth quarter (January-March 2018), i.e. there is still room for major improvements in technical efficiency.

## 5. Conclusion

This study investigated the technical efficiency of dairy family farmers assisted by a climate resilience programme (MAIS) in the Brazilian semi-arid region. The programme created an agricultural system aiming to regenerate the local ecosystem services and build climate resilience through the adoption of smart production practices and locally adapted and low-cost technologies.

Results indicated that the smallholder farmers assisted by the programme improved their average milk production during the 2016–2018 period by nearly 10% per quarter, while the frontier of production increased by nearly 7% per quarter. We also identified that a milk cooling system<sup>10</sup> might remarkably increase both the average and the frontier of production. However, temperature shocks are the main threat to the farmers' efficiency. Our findings confirm the importance of agro-climatic conditions on total factor productivity (Demir & Mahmud, 2002; Mukherjee et al., 2013; Njuki et al., 2020; Perez-Mendez et al., 2019).

Technical efficiency also grew in the period of analysis (7 percentage points). Although we can not infer causality, the programme duration is also associated with improvements in farmers' efficiency. Because technical efficiency is a measure of how much a farmer can do with what they have, the findings suggest that the programme may have contributed to farmers' resilience: a farmer able to achieve higher system productivity creates more of a buffer to absorb climate shocks to the system. In addition to impacting the depth of shock's impact, better technical efficiency through practices aimed at maintaining a

robust farm ecosystem will also impact the time to recovery from a shock in a positive way. In sum, the adoption of smart production practices can enhance production capacity and engage farms in production that is not depleting the natural capital.

The analysis's main limitation is that our sample is restricted to a small group of beneficiary farmers. In this respect, our study is limited in its ability to address any causal relationship between participation in the programme and improvements in milk production and technical efficiency. In other words, we can not necessarily infer that improvements in milk production and technical efficiency were solely due to the participation in the MAIS programme. Also, we used a production function instead of a profit function because, for family farmers, it is tough to separate business from all of life. That is, it would be challenging to understand inputs/costs and outputs/revenues without an entire comprehensive household budget/accounting.

Nonetheless, one main contribution of this study is to demonstrate that "best practices" can be relevant in alleviating the impacts of climate change on impoverished family farmers. The average production and technical efficiency of family farmers substantially improved with the duration of a locally-adapted technical orientation. Insights from this research can help policymakers to formulate strategies related to climate resilience in semi-arid regions. In this context, some factors (such as technical extension services, credit to access new technologies, education, and weather information) must be considered when designing and implementing policies since they contribute to overcoming financial and information barriers, enhancing the use of climate change adaptative practices (Shahzad & Abdulai, 2020). Moreover, the results offer interesting points for academic discussion regarding both the identification of vulnerable areas and the analysis of strategies to improve coping strategies and the adaptive capacity of farmers.

## Notes

1. The main biome of the Brazilian *Sertão* is known as Caatinga – an exclusively Brazilian biome that occupies about 10% of the national territory and 50% of the state of Bahia. It is characterized by a semi-arid climate, diverse landscape, desert vegetation adapted for long periods of drought, and high biodiversity (Beuchle et al., 2015).
2. The Human Development Index (HDI) of the municipalities of JBA ranged, in 2010, between 0.53 and 0.63 – similar to those observed in many Sub-Saharan African countries. The Gross Domestic Product (GDP) per capita was 75% lower than the Brazilian average. Further, almost 80% of the population has completed no more than basic primary education.
3. The average land size in the area (29 hectares) was far below the average in the state of Bahia (36 hectares) and Brazil (69 hectares). The JBA produced an annual average of 58 thousand liters of milk between 2010 and 2018, accounting for 5.5% of Bahia state's total production and 0.2% of the Brazilian production. During this period, the average yield was 705 liters/cow in the JBA, 8% (56%) lower than the state (national) indices (IBGE, 2020).
4. The milk production in the Jacuípe Basin mainly involves family farmers. The Brazilian Federal Law No. 11,326 of 2006 defines a family farmers those satisfying the following criteria: (i) the farm size cannot be larger than four (official) modules - the module varies from 50 to 60 hectares for the municipalities of the JBA; ii) the

farm is managed by the own family; iii) the labor force comes predominantly from the own family; iv) the family income comes predominantly from the own farm.

5. The use of *Opuntia-Ficus Indica* as a feed supplement for the livestock played a key role in the program. The cactus (*Opuntia*) presents a great adaptation in semiarid areas, since it is a low-water requirement plant. Despite the low protein content, the *Opuntia* has high content of carbohydrates and provides a relevant proportion of livestock's water requirement. Further, since the cactus represents a lower cost feed (compared to corn, for example) and presents high water use efficiency, its use contributes to enhance semi-arid region sustainability (Andrade-Montemayor et al., 2011).
6. We summed the total production of milk per quarter and divided by 3.
7. We did not consider family labor, since this variable showed many null values – probably because farmers misunderstood the question and did not recognize family members as labor force.
8. We do not use log of labor because 35% of the total number of observations are zero.
9. The larger the number of regressors ( $x$ ), the lower the farmers' unobservable heterogeneity ( $c$ ).
10. Milk cooling systems increase the farmers' capacity to store milk and eventually sell it at a higher price, which brings more cash to invest in the farm. That is, cooling systems are directly related to milk quality.

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## Disclosure statement

No potential conflict of interest was reported by the author(s).

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## Appendix A.

**Table A1.** Frontier model results for log of milk production with seasonal component (binaries for calendar quarters). Sampled farmers between the 1st quarter of 2016 and the 1st quarter of 2018.

	Model 3-A	Model 3-B
	Frontier of production (log of milk)	
Quarters	0.068*** (0.016)	0.065*** (0.018)
In size	0.154 (0.146)	0.148 (0.138)
Labour	0.064*** (0.012)	0.066*** (0.012)
Investment	0.160* (0.074)	0.159* (0.073)
Cistern	0.084 (0.107)	0.078 (0.104)
Tractor	0.094 (0.114)	0.092 (0.113)
Cooling	0.229** (0.089)	0.231** (0.088)
Calendar quarters (binaries)	yes	yes
	technical inefficiency ( $\mu$ )	
Z-temperature		0.255 (0.164)
Z-precipitation		0.207 (0.173)
N	206	206
$\sigma_u$	0.362*	0.300
$\sigma_v$	0.302***	0.300***
$\lambda = \sigma_u/\sigma_v$	1.200***	1.001***
Log likelihood	−88.1	−87.4

Notes: \*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$ . Standard errors in parentheses.  $\sigma_u$  is the standard deviation of the component associated with the technological inefficiency and  $\sigma_v$  is the standard deviation of the idiosyncratic error. Estimates for the frontier of production refer to the main effect of each variable at the means of covariates.