TECHNICAL EFFICIENCY OF FAMILY DAIRY FARMS:
THE EXPERIENCE OF A CLIMATE RESILIENCE PROGRAM IN BRAZIL

Alexandre Gori Maia
Department of Economics
University of Campinas, Brazil
E-mail: gori@unicamp.br

Camila Veneo Campos Fonseca
Faculdades de Campinas
Facamp, Brazil
E-mail: camila.veneo@facamp.com.br

Rodrigo Lanna Franco da Silveira
Department of Economics
University of Campinas, Brazil
E-mail: rlanna@unicamp.br

Jennifer Burney
University of California, San Diego (IRPS)
San Diego, USA
E-mail: jburney@ucsd.edu

Daniele Cesano
REDEH-Rede de Desenvolvimento Humano
Rio de Janeiro, Brazil
E-mail: daniele.cesano@gmail.com

Selected Paper prepared for presentation at the 2019 Agricultural & Applied Economics Association Annual Meeting, Atlanta, GA, July 21-23

TECHNICAL EFFICIENCY OF FAMILY DAIRY FARMS: THE EXPERIENCE OF A CLIMATE RESILIENCE PROGRAM IN BRAZIL

ABSTRACT

This paper investigates the dynamics and determinants of technical efficiency of dairy farmers assisted by a climate resilience program in the Brazilian semi-arid region. We use stochastic frontier models applied to a panel of 43 family farmers during nine quarters, considering productive and technological factors that potentially improve production and efficiency. Our estimates showed that the milk production increased by an average of 10% per quarter, while the access to basic technologies remarkably improved the farmer's technical efficiency.

Keywords: technical efficiency, climate resilience, dairy farms.

1. INTRODUCTION

Family farmers in the semi-arid region of Brazil are extremely vulnerable to climate change. This scenario is explained by a combination of factors including advanced desertification, land degradation, rainfall deficits, water scarcity, and precarious socioeconomic 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 (MARENGO et al. 2017). In addition, climate forecasts indicate worsening conditions related to rainfall deficits and soil aridity in this region during the second half of the 21st century (IPCC, 2014).

Several studies have investigated the impact of climate change on agricultural production in different regions of the world (Mendelsohn and Dinar 2009; Pires et al. 2016; Key and Sneeringer 2014; Hannah et al. 2017). More recently, studies have focused on how adaptive strategies may offset the negative impacts of climate change on production and food security (Smit and Wandel 2006; Falco, Veronesi, and Yesuf 2011; Oumer 2019; de Sousa et al. 2018). 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.

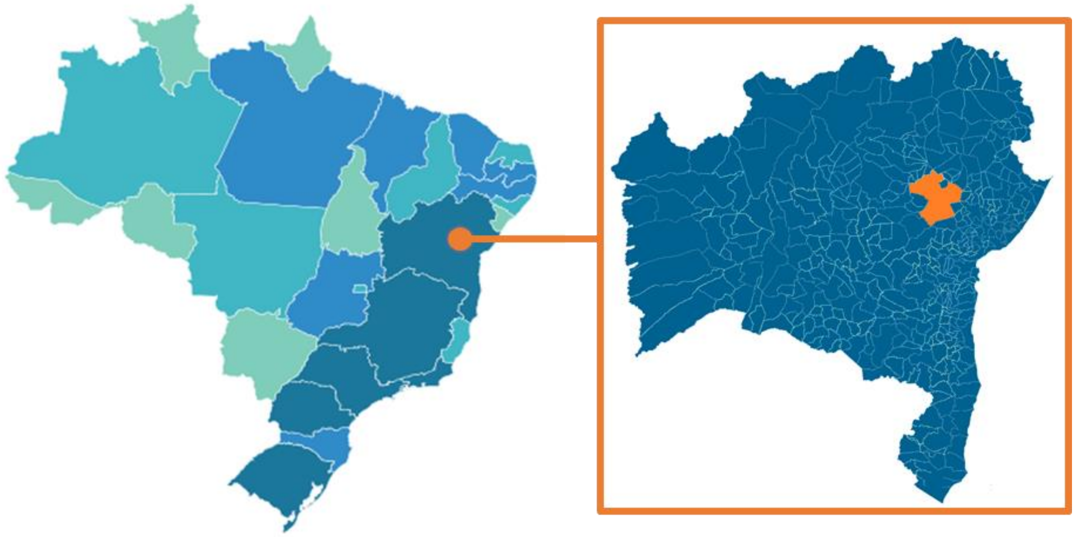
However, specific experiences have shown that the adoption of basic management practices may bring remarkable economic gains to family famers facing yield-limiting factors. In this context, several programs have been formulated to help counteract the effects of climate changes on vulnerable rural areas, aiming to enhance the resilience of smallholder farmers. Muluneh et al. (2017), for example, evaluated adaption strategies used in the Rift Valley dry lands of Ethiopia. Results indicated that supplemental irrigation seems to reduce the negative effects of climate change, improving food security. Focusing on other sub-Saharan African countries – Zambia and Kenya, respectively –, Khonje et al. (2018) and Wainaina et al. (2018) explored the adoption of multiple agriculture technologies, indicating positive impacts on farmers' household income. In addition, Zhang et al. (2016) evaluated the implementation of the Science and Technology Backyard (STB) platform in China. Considering the group of famers who faced yield-limiting factors, the adoption of recommended management practices improved the productive performance, allowing farmers to achieve higher yield and economic gains. Burney et al. (2014) contributed to this debate, analyzing the case of dairy farmers in the Brazilian semi-arid region. Overall, the use of efficient irrigation systems and balanced animal diet practices improved profitability, productivity, as well as the net income.

This study investigates the dynamics and determinants of production and technical efficiency of family dairy farmers assisted by a climate resilience program in the Brazilian semi-arid region. The program is called MAIS, *Módulo Agroclimático Inteligente e Sustentátvel*, which means Sustainable Smart Agro-climatic Module. In 2016, the MAIS program implemented an innovative 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. The central idea of our study is therefore to identify how family farmers can maximize their feasible production given only a bundle of limited but strategically selected inputs and technologies.

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 (denominated by Brazilian *Sertão*), which is plagued by poor socioeconomic indicators, food insecurity, and high level of poverty and inequality (Gori Maia et al. 2018).

Figure 1. Geographical location of Jacuípe basin area (JBA).



Source: IBGE (2019)

The JBA covers 10,739 km^2 and contains 14 municipalities, with a total population of 238,127 people in 2018 (Table 1). The region presents extremely low levels of socioeconomic development. The Human Development Index (HDI) of the municipalities ranged, in 2010, between 0.53 and 0.63 – similar to those observed in many Sub-Saharan African countries (such as Kenya, Zambia, Ghana, and Congo). Almost 80 percent of the population presented no more than basic primary education. The Gross Domestic Product (GDP) per capita of the JBA reached, in 2016, $2,135 USD, which was 75% lower than the national average.

Table 1. Socioeconomic characteristics of Jacuípe basin municipalities.

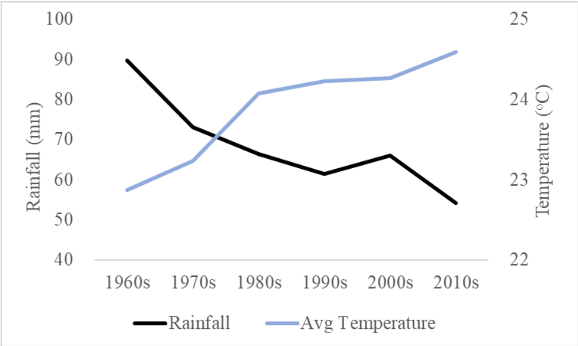
Municipality	Area (km^2)	Population[a]	People/km^2	HDI[b]	GDP per capita (USD)[c]
Baixa Grande	968	20,488	21.18	0.585	1,833
Capela do Alto Alegre	630	11,660	18.52	0.599	1,907
Gavião	385	4,487	11.67	0.599	2,275
Ipirá	3,105	59,763	19.25	0.549	3,158
Mairi	907	18,753	20.68	0.572	1,867
Nova Fátima	347	7,802	22.50	0.597	2,466
Pé de Serra	597	13,601	22.79	0.587	1,920
Pintadas	647	10,482	16.20	0.612	1,994
Quixabeira	366	8,990	24.54	0.578	1,800
Riachão do Jacuípe	1,155	33,403	28.91	0.628	2,674
São José do Jacuípe	362	10,417	28.75	0.552	2,088
Serra Preta	595	15,064	25.30	0.566	1,770
Várzea da Roça	468	14,087	30.07	0.539	1,721
Várzea do Poço	206	9,130	44.22	0.575	2,423
Jacuípe basin area	**10,739**	**238,127**	**22.17**	**0.578**	**2,135**
Bahia state	**564,722**	**14,812,617**	**26.23**	**0.660**	**4,837**
Brazil	**8,510,820**	**208,494,900**	**24.50**	**0.699**	**8,688**

Notes: [a] Estimated population in 2018; [b] Municipal Human Development Index in 2010; GDP per capita observed in 2016, considering an exchange rate of R$3.50/USD.
Source: IBGE (2019)

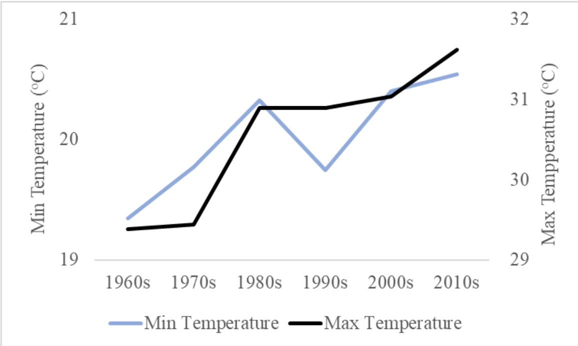
The main activities in the region are the extensive livestock and dairy farming. According to the 2017 Agricultural Census, the region hosts more than 20,000 smallholder farmers with a land size of less than 50 hectares, who represents 88 per cent of the total farmers in the region. Almost 50 per cent of these farmers have never had a formal education (compared with 32 per cent of all famers in Brazil) and only 10 per cent received technical assistance (compared with 18 per cent of all farmers in Brazil). The average milk production in the region (1.4 thousand liters/cow/year) is 45% lower than the national average.

The region has been severely hit by increasing temperatures and recurrent droughts. Between 1961 and 2018, the average temperature increased by 0.4°C per decade, reaching a minimum (maximum) average of 21°C (31°C) in 2010s (Figure 2). The region has also historically suffered with 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.

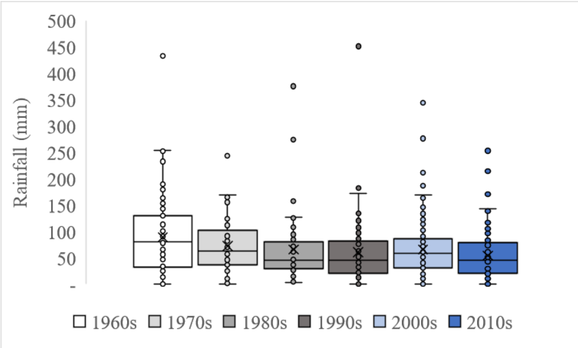
Figure 2. Evolution of monthly rainfall and temperature indices between 1960s and 2010s.[a]



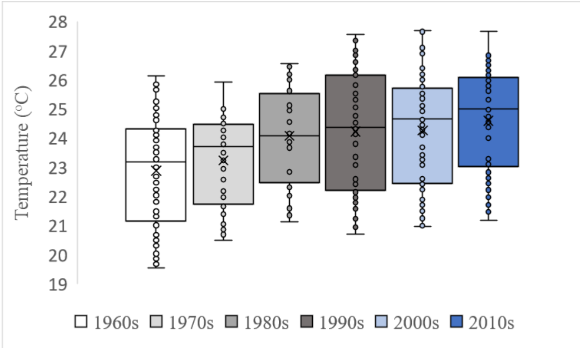
(a) Average monthly rainfall and temperature



(b) Average monthly min. and max. temperature



(c) Boxplot: monthly rainfall



(d) Boxplot: monthly average temperature

[a] Note: the dataset of monthly precipitation and temperature indices come from Serrinha municipality, the closest meteorological station of JBA (for example, 32 miles from Riachão do Jacuípe municipality).
Source: INMET (2017)

In 2014, a multi-stakeholder called "*Adapta Sertão*" created the MAIS program (*Módulo Agroclimático Inteligente e Sustentável*, or Sustainable Smart Agro-climatic Module). The key goal of the MAIS was to enhance farmers' adaptive capacities to climate change using efficient and low-cost technologies and production practices, along with market integration strategies. The program 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 program assisted 100 family farmers in their milk and sheep meat production in the JBA. The MAIS created an agricultural program that aims to regenerate the local ecosystem services and build climate resilience through the adoption of smart production practices and locally adapted technologies (Voigtlaender, Magalhães, and Rizzi 2017). The MAIS program was implemented through four interrelated steps:

1. Development of a modules of production using specific technologies and strategies. The basic module's characteristics were minimum area of production (20 hectares) to guarantee a sustainable provision of pastures, area for Livestock-Forest-Pasture integration, area for hay production and forage, mainly Opuntia-Ficus Indica (a cactus); a maximum number of heads per module to guarantee a sustainable production in the long run without the depletion of natural resources, especially soil; best animal management practices; a management center designed to promote a sustainable intensification of the livestock production and reduce the animal heat stress; construction of wells, water cisterns and earth damns to ensure family and animal water needs during prolonged droughts; recommendation of small-scale and low-cost machineries, especially those with a high aggregated labor value, to reduce manual work; technical assistance to train farmers in the proper implementation and management of the production system.

2. Technical assistance: each field technician received technical training to help farmers to implement the module over a period of two to three years through monthly four hours visits. The technicians were managed by the MAIS program coordinators, i.e. senior consultants with a consolidated experience in the implementation and training of the different MAIS practices and project coordination.

3. Financial orientation: the MAIS program included a financial orientation plan in order to implement the modules, considering four basic points: (i) selling of unused assets; (ii) investment of farmers' savings; (iii) access to government incentives/subsidies to agriculture; (iv) access to credit programs.

4. Monitoring and evaluation: each farm was monitored and evaluated through the collection of quantitative and qualitative technical, economic, environmental and production data.

3. MATERIAL AND METHODS

3.1. DATA SOURCE

Our analysis was based on a panel with monthly data for 43 dairy farmers assisted by the MAIS program between January 2016 and March 2018. The interviews were carried out by four technicians trained by the MAIS program, who were also responsible for the technical assistance of the family farmers. In order to reduce volatility and missing values, we aggregated the monthly data in quarters, considering the mean in each period.

We were interested in understanding the determinants of the technical efficiency of the variable production of milk per month (*milk*, in liters). The inputs of production provided by our panel data were: a) farm size (*size*, in hectares); b) cost of hired labor (*labor*, in constant Brazilian Reais, BRL), taking into account exclusively temporary and permanent labor[1]; c) total investments (*invest*, in constant Brazilian Reais, BRL). We also calculated the number of quarters each farmer stayed in the program (*quarters*), a proxy for the learning gains provided by the MAIS program. We also obtained information for the farm infrastructure and access to technology: a) *cistern*, a binary variable that equals 1 for the presence of water cistern in the farm; b) *tractor*, a binary variable that equals 1 for the presence of a 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 refer exclusively to the first quarter of 2018.

Table 2 presents the descriptive statistics. The average milk production was 3.4 thousand litters per month, while the average farm area was 42.2 hectares. The data also reveal that the average investment level was $476.9 BRL per month ($109.38 USD) with a standard deviation that was almost 2.5 times larger than the average: $1,158.3 BRL ($336.06 USD)[2]. This finding suggests the presence of a relevant heterogeneity in both farmers' investment capacity and farmers' preference towards investment decision.

With respect to the use of labor force (permanent and temporary labor, excluding family labor), the average cost was $394.7 BRL per month ($114.54 USD), with a standard deviation of $458.3 BRL ($133 USD). Approximately one third of the farmers used

[1] We did not consider family labor, since this variable showed many null values – probably because producers do not recognize family members as labor force.

[2] Considering an exchange rate average of $3.45 BRL/USD, from 2016-2018 period.

exclusively family labor during more than two quarters of the fieldwork. Further, the technology adoption in the production system was limited. While around one third of the farmers had a milk cooling system, only 15 per cent had a brush cutter. Furthermore, only 34 per cent of the farmers had a source of water in order to ensure family and animal needs during prolonged droughts. Finally, the average period of participation in the MAIS program was 3.6 quarters – the number of the farmers in the program increased from 4 in the first quarter of 2016 to 39 in the first quarter of 2018.

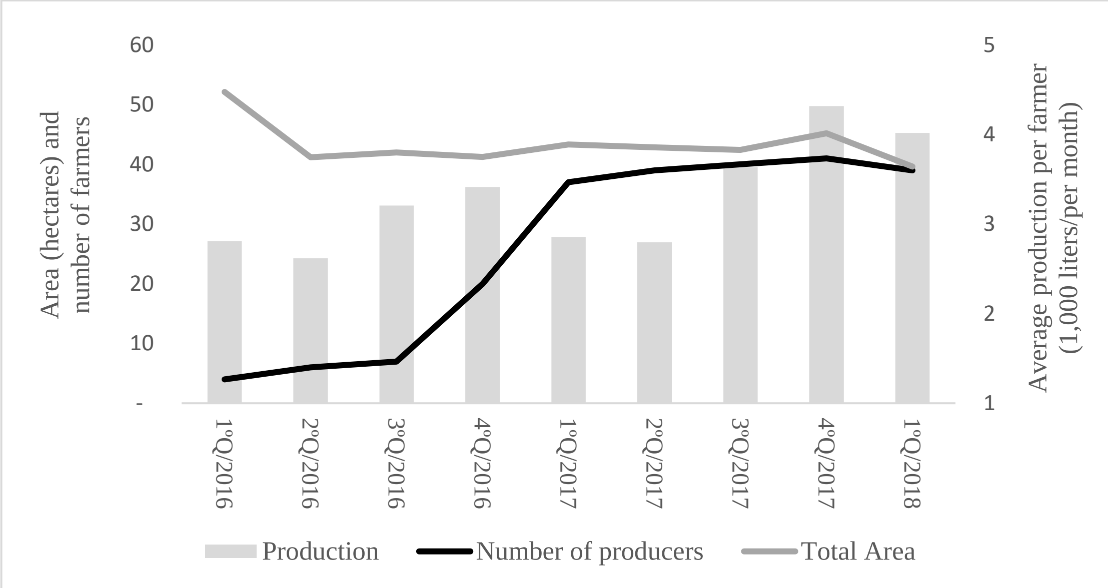
Table 2. Descriptive statistics of the collected variables.

Variables	Obs.	Average	Std. Dev.	Min	Max
Produced Milk (liters per month)	235	3,449.61	2,252.00	60.00	13,515.00
Farm area (hectares)	239	42.22	28.52	11.00	120.00
Cost of hired labor (BRL/per month)	239	394.73	458.29	0.00	2,000.00
Total investment (BRL/per month)	239	476.85	1,158.28	0.00	8,102.00
Water source (binary variable)	210	0.25	0.43	0.00	1.00
Tractor (binary variable)	210	0.15	0.36	0.00	1.00
Milk cooling system (binary variable)	210	0.34	0.48	0.00	1.00
Participation in the program (quarters)	239	3.55	2.00	1.00	9.00

Source: survey data

Most farmers joined the MAIS program between the 3rd quarter of 2016 and 1st quarter of 2017 (Figure 3). The average area size did not change remarkably in this period. However, MAIS farmers improved remarkably their total milk production between 2016 and 2018, from 2.8 to 4.0 thousand liters per month (43%). During this period, the milk production per hectare increased almost twofold, from 54 to 101 liters/hectare, i.e., there was a meaningful intensification of the milk production. The econometric models presented in the next section provide a detailed analysis of this issue and shed more light on the discussion.

Figure 3. Average milk production (1,000 liters per month), average area (hectare) and total number of farmers between 2016 and 2018.



Source: Survey data

3.2. EMPIRICAL STRATEGY

We used stochastic frontier (SF) models to analyze the technical efficiency of the MAIS farmers. The SF models allowed us: i) to evaluate how close the farmers were to the maximum productive efficiency; ii) to identify the determinants of the technical inefficiency in the production. The SF models were initially developed by Aigner et al. (1977) and Meeusen and Broeck (1977) to estimate the inefficiency associated to a traditional function of production (or cost). In other words, when y_{it} is the production (*milk*) of the farm i in quarter t and $\mathbf{x_{it}}$ a vector of k explanatory factors (inputs), the function of production is given by:

$$lny_{it} = \mathbf{x}_{it}\beta + \delta t + c_i + e_{it} \quad i = 1, .., n \tag{1}$$

The coefficient δ is a measure of the farmers' average learning gains, i.e., the improvements in farmers' production per quarter of duration of the MAIS program. The component c_i is the unobservable farmer heterogeneity (for example, agricultural skills and attitude towards agricultural innovations), which can be controlled by random or fixed effects (Greene 2005). The SF model allows us to disaggregate the error e_{it} into two specific components: i) aleatory shocks (v_{it}), resultant, for example, from unexpected or unobserved factor; ii) components associated to technological inefficiency (u_{it}). In other words:

$$lny_{it} = \mathbf{x}_{it}\beta + \delta t + c_i + v_{it} - u_{it} \qquad (2)$$

The shock v_{it} is assumed to be independent and identically distributed, and independent of u_{it}. The component u_{it} is positive and represents the technological inefficiency. In other words, u_{it} represents a decrease in relation to the maximum feasible production. The component u_i can also be represented by a function of a vector $\mathbf{z}_i$ of observable characteristics, such as access to technology and production practices (Battese and Coelli 1995). In other words, we will have:

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

$$\mu_{it} = \mathbf{z}_{it}\emptyset \qquad (4)$$

In this case, u_i presents normal positive distribution with an average value μ_i conditional to the characteristics $\mathbf{z}_{it}$, and $\emptyset$ is a vector of coefficients to be estimated. The estimation strategy consists of maximizing the function of log-likelihood conditioned to the vector of coefficients $\boldsymbol{\beta}$ and $\emptyset$, and to the parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$, where σ_v^2 is the variance of v (Battese and Coelli 1995).

In addition to defining the determinants of the production and efficiency, a particularly useful analysis in the SF model is the estimation of the technical efficiency. Based on equation (2), the production y_{it} can be given by the product of three components:

$$y_{it} = \exp(\mathbf{x}_{it}\beta + \delta t + c_i) \times \exp(v_{it}) \times \exp(-u_{it}) \qquad (5)$$

The product of the first two components defines the production possibility frontier, i.e. the level of production considering a hypothesis of total productive efficiency. In turn, the inefficiency component $\exp(-u_i)$ represents the distance in relation to the production possibility frontier that is a result of inefficiency. Based on this analysis, we can extract one of the most common measures of technical efficiency, TE_i (Coelli, Rao, and Battese 1998):

$$TE_{it} = \frac{y_{it}}{\exp(\mathbf{x}_{it}\beta + \delta t + c_i) \times \exp(v_{it})} = \exp(-u_{it}) \qquad (6)$$

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

4. RESULTS

We first checked the consistency of the estimates using random effects (RE) and fixed effects (FE) by the Hausman test (Appendix A). Differences between fixed and random effect estimates were insignificant, suggesting the efficiency of the latter estimates.

Table 3 reports the estimates for equation (1) using three different specifications: Model 1, which regresses milk production exclusively as a function of the duration of the MAIS program (t) as explanatory variable; Model 2, which controls for the main inputs of milk production ($area$, $labor$ and $invest$); Model 3, which controls for the access to technology ($cistern$, $tractor$ and $cooling$). The statistics of goodness of fit improved remarkably once we control for the inputs of production and access to basic technologies: R^2 ranging from 6.5% in Model 1 to 35.7% in Model 3. More importantly, the estimates for the net impacts of the duration of the MAIS program (t) tended to be robust to different specifications. Results indicated that the time of the MAIS program had a positive and significant impact on dairy farming: the milk production increased by an average of 10% for each quarter of technical assistance provided by the MAIS program.

Hired labor tended to have small but significant effects on the dairy production. For example, the estimates from Model 2 suggest that the milk production tended to increase by 0.05% for each 1% increase in the cost of hired labor. The net effect of area was only significant once we controlled for the access to technology (Model 3): the average production increased by 0.16% for each 1% increase in the total area. With respect to the access to technology, estimates indicate that access to water cistern ($cistern$) and milk cooling system ($cooling$) presented the most significant net effects on dairy production: nearly 34% ($e^{0.29} - 1 = 0.34$) of increase in the average production in the case of access to any of these technologies.

Table 3. Random effect estimates

Variables	Model 1		Model 2		Model 3	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
t	0,1054***	-0,013	0.1070 ***	(0.012)	0.0995 ***	(0.011)
ln *area*			0.0800	(0.108)	0.1636 **	(0.089)
ln *labor*			0.0547 ***	(0.013)	0.0348 ***	(0.011)
ln *invest*			0.0157 *	(0.008)	0.0070	(0.007)
Cistern					0.2933 *	(0.159)
Tractor					0.1436	(0.191)
Cooling					0.2937 *	(0.151)
constant	7,5647***	-0,118	70.165 ***	(0.400)	67.073 ***	(0.350)
n	235		235		206	
R^2	0.0647		0.2529		0.3567	

Source: survey data;
*** p<0.001; ** p<0.01; * p<0.05; + p<0.10

Once we have analyzed random-effect models for a traditional production function, we evaluated the farmers' technical inefficiency through SF models (equation 2). We defined land, labor, and investment as the inputs of production (**x** in equation 2), while the access to technology were defined as determinants of the technical efficiency (**z** in equation 4). As a general assumption for this analysis, we would expect that producers with access to basic technologies could remarkably improve efficiency if this access was linked to a well-structured and planned technical assistance program.

Table 4 presents the estimates for the SF models, considering two different specifications: Model 1, which considers that the technical inefficiency is independent of exogenous technologies; Model 2, which includes the determinants of technical inefficiency (**z** in equation 2). Once we did not find evidences of correlation between regressors **x** and the farmers unobservable heterogeneity (c_i) in prior analyses, estimates in Table 4 were obtained using *True Random Effects* (Greene 2005). Results highlighted that the inefficiency component (u_{it}) played an important role in the models for milk production: the variability of this component (σ_u) was significantly different from zero in both models and was between 2.3 and 3.6 larger than the variability of the random error (σ_v).

Table 4. Frontier model results

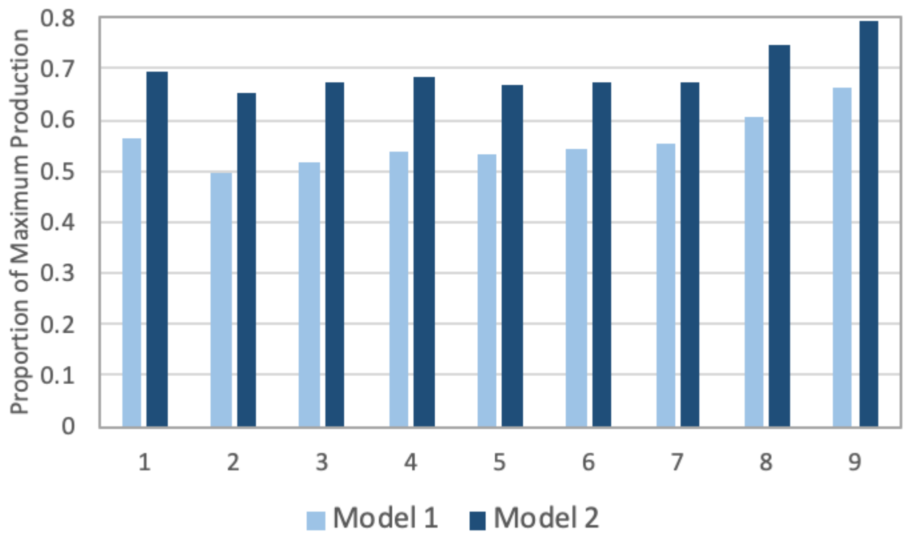
Production function – Variables				
	Model 1		Model 2	
	Coef.	s.e.	Coef.	s.e.
t	0.0800***	(0.017)	0.0841***	(0.016)
ln *area*	0.1934***	(0.064)	0.2058***	(0.062)
ln *labor*	0.0621***	(0.013)	0.0619***	(0.013)
ln *invest*	0.0333***	(0.011)	0.0270***	(0.010)
constant	7.3450***	(0.219)	7.0662***	(0.216)
Technical Inefficiency – Variables				
	Coef.	s.e.	Coef.	s.e.
cistern			-1.3400**	(0,655)
tractor			-0.7779**	(0,779)
cooling			-1.7130*	(0,673)
constant			0	omitted
σ_u	0.9652***	(0.065)	0.7881***	(0,114)
σ_v	0.2655***	(0.038)	0.3410***	(0,047)
$\lambda = \sigma_u / \sigma_v$	3.6354***	(0.089)	2.3109***	(0,150)
Log likelihood	-214.2900		-139.5497	
N	235		206	
Number of groups	43		37	

Source: survey data;
*** p<0.001; ** p<0.01; * p<0.05; + p<0.10

All estimates, in both Models 1 and 2, were also significant at 5% level. The duration of the technical assistance provided by the MAIS program showed to improve the milk production by an average of 8% per quarter. Additionally, farm size, hired labor and investment had also significant impacts on dairy production: elasticities equal to 0.21%, 0.06% and 0.03%, respectively. Findings also highlighted that the access to strategically selected technologies – water supply, tractor and milk cooling system – could remarkably improve the farmer's technical efficiency. The most significant determinants of technical efficiency were: access to a milk cooling system (reduced inefficiency by 82%, since $e^{-1.71} - 1 = 0.82$); presence of water cistern tanks with a storage capacity of at least 50,000 liters (reduced inefficiency by 74%); use of tractor (reduced inefficiency by 54%). Average technical efficiency ranged from 56% to 69% in the first quarter of participation in the MAIS program; and from 66% to 79% in the final, ninth quarter of participation.

Finally, we estimated the farmers' technical efficiency (TE) in each quarter of technical assistance using equation 6. Figure 4 presents the estimates for each model. The TE increased from 0.56 in the quarter 1 to 0.66 in the quarter 9 according to the estimates for Model 1. The TE naturally increases once we control for the access to technology (Model 2), ranging from 0.69 to 0.79. The most notable improvements occurred after the second year in the program (quarter 8), when technical efficiency increased by nearly 6 percentage points in Model 1 and 7 percentage points in Model 2.

Figure 4. Technical efficiency in the milk production



Source: Survey data

5. CONCLUSION

This study investigated the dynamics and determinants of production and technical efficiency of family dairy farmers assisted by a climate resilience program (MAIS) in the Brazilian semi-arid region. Results indicated that the smallholder farmers assisted by the MAIS program improved their dairy production remarkably during the 2016-2018 period. The estimates of our panel data models showed that the milk production increased by an average of 10% for each quarter. In addition, findings from SF models indicated that access to basic technologies can remarkably improve farmer's technical efficiency.

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, as well as their dependence on scarce water resources in the region. Nonetheless, our study indicated that the implementation of a climate resilience program had an important effect on dairy production. In general, as argued by Zhang et al. (2016), it is possible to propose affordable adaptive strategies that are efficient and easily assimilated by small producers. Particularly considering MAIS program, locally adapted and low-cost technologies, such as a minimum capacity of water storage, milk cooling system and use of a tractor, have shown capable to reduce farmers' technical inefficiency, enabling smallholder farmers to sustainably achieve environmental sustainability and productive gains.

One main limitation of our analysis is that our sample is restricted to a small group of beneficiary farmers. In this respect, our purpose is not decidedly to establish a causal relationship between participation in the program and improvements in dairy production and technical efficiency. Non-MAIS dairy farmers, who are not considered in our sample, may have also had substantial improvement in their dairy production. However, this is a remote possibility, as official data show that total dairy production in the region decreased by 4% between 2016 and 2017.

The 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 dairy farmers substantially improved with a locally-adapted technical orientation. Insights from this research can be particularly helpful for policymakers in formulating strategies related to climate resilience in semi-arid regions. Moreover, the results offer interesting points for academic discussion regarding both the identification of vulnerable areas and a respective analysis of strategies to improve coping strategies and the adaptive capacity of farmers.

REFERENCES

Aigner, Dennis, C.A.Knox Lovell, and Peter Schmidt. 1977. "Formulation and Estimation of Stochastic Frontier Production Function Models." *Journal of Econometrics* 6 (1):21–37. https://doi.org/10.1016/0304-4076(77)90052-5.

Battese, G. E., and T. J. Coelli. 1995. "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data." *Empirical Economics* 20 (2):325–32. https://doi.org/10.1007/BF01205442.

Burney, Jennifer, Daniele Cesano, Jarrod Russell, Emilio Lèvre La Rovere, Thais Corral, Nereide Segala Coelho, and Laise Santos. 2014. “Climate Change Adaptation Strategies for Smallholder Farmers in the Brazilian Sertão.” *Climatic Change* 126 (1–2):45–59. https://doi.org/10.1007/s10584-014-1186-0.

Coelli, Tim, D. S. P. Rao, and George E. Battese. 1998. *An Introduction to Efficiency and Productivity Analysis*. Boston: Kluwer Academic Publishers.

Falco, Salvatore Di, Marcella Veronesi, and Mahmud Yesuf. 2011. “Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia.” *American Journal of Agricultural Economics* 93 (3):829–46. https://doi.org/10.1093/ajae/aar006.

Gori Maia, Alexandre, Daniele Cesano, Bruno Cesar Brito Miyamoto, Gabriela Santos Eusebio, and Patricia Andrade de Oliveira Silva. 2018. “Climate Change and Farm-Level Adaptation: The Brazilian Sertão.” *International Journal of Climate Change Strategies and Management*, April, IJCCSM-04-2017-0088. https://doi.org/10.1108/IJCCSM-04-2017-0088.

Greene, Willam. 2005. “Fixed and Random Effects in Stochastic Frontier Models.” *Journal of Productivity Analysis* 23 (1):7–32. https://doi.org/10.1007/s11123-004-8545-1.

Hannah, Lee, Camila I. Donatti, Celia A. Harvey, Eric Alfaro, Daniel Andres Rodriguez, Claudia Bouroncle, Edwin Castellanos, et al. 2017. “Regional Modeling of Climate Change Impacts on Smallholder Agriculture and Ecosystems in Central America.” *Climatic Change* 141 (1):29–45. https://doi.org/10.1007/s10584-016-1867-y.

INMET. 2017. “Portal Do INMET - Instituto Nacional de Meteorologia.” 2017.

Instituto Brasileiro de Geografia e Estatística. 2019. “Portal Do IBGE.” 2019.

Intergovernmental Panel on Climate Change. 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. *IPCC*. Geneva: IPCC.

Key, N., and S. Sneeringer. 2014. “Potential Effects of Climate Change on the Productivity of U.S. Dairies.” *American Journal of Agricultural Economics* 96 (4):1136–56. https://doi.org/10.1093/ajae/aau002.

Khonje, Makaiko G., Julius Manda, Petros Mkandawire, Adane Hirpa Tufa, and Arega D. Alene. 2018. “Adoption and Welfare Impacts of Multiple Agricultural

Technologies: Evidence from Eastern Zambia." *Agricultural Economics* 49 (5):599–609. https://doi.org/10.1111/agec.12445.

Marengo, José A., Lincoln M. Alves, Regina C.S Alvala, Ana Paula Cunha, Sheila Brito, and Osvaldo L.L. Moraes. 2017. "Climatic Characteristics of the 2010-2016 Drought in the Semiarid Northeast Brazil Region." *Anais Da Academia Brasileira de Ciências* 90 (2 suppl 1):1973–85. https://doi.org/10.1590/0001-3765201720170206.

Meeusen, Wim, and Julien van Den Broeck. 1977. "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error." *International Economic Review* 18 (2):435. https://doi.org/10.2307/2525757.

Mendelsohn, Robert, and Ariel Dinar. 2009. *Climate Change and Agriculture: An Economic Analysis of Global Impacts, Adaptation and Distributional Effects*. Cheltenham: Edward Elgar.

Muluneh, A., L. Stroosnijder, S. Keestra, and B. Biazin. 2017. "Adapting to Climate Change for Food Security in the Rift Valley Dry Lands of Ethiopia: Supplemental Irrigation, Plant Density and Sowing Date." *The Journal of Agricultural Science* 155 (5):703–24. https://doi.org/10.1017/S0021859616000897.

Oumer, Ali M. 2019. "Climate Smart Agriculture: Building Resilience to Climate Change, Edited by L.Lipper, N.McCarty, D.Zilberman, S.Asfaw and G.Branca. Published by Springer International, 2018, Pp. 630, ISBN: 978-3-319-61193-8, Open Access under a CC BY-NC-SA 3.0 IGO Licens." *Australian Journal of Agricultural and Resource Economics* 63 (1):198–200. https://doi.org/10.1111/1467-8489.12294.

Pires, G. F., G. M. Abrahão, L. M. Brumatti, L. J. C. Oliveira, M. H. Costa, S. Liddicoat, E Kato, and R. J. Ladle. 2016. "Increased Climate Risk in Brazilian Double Cropping Agriculture Systems: Implications for Land Use in Northern Brazil." *Agricultural and Forest Meteorology* 228–229 (15):286–98. https://doi.org/10.1016/j.agrformet.2016.07.005.

Smit, Barry, and Johanna Wandel. 2006. "Adaptation, Adaptive Capacity and Vulnerability." *Global Environmental Change* 16 (3):282–92. https://doi.org/10.1016/j.gloenvcha.2006.03.008.

Sousa, Kauê de, Fernando Casanoves, Jorge Sellare, Alejandra Ospina, Jose Gabriel

Suchini, Amilcar Aguilar, and Leida Mercado. 2018. “How Climate Awareness Influences Farmers’ Adaptation Decisions in Central America?” *Journal of Rural Studies* 64 (November):11–19. https://doi.org/10.1016/j.jrurstud.2018.09.018.

Voigtlaender, Maureen, Clarissa Magalhães, and Julia A. Rizzi. 2017. “Projeto Adapta Sertão - Relatório de Avaliação Intermediária.” Saltinho-SP.

Wainaina, Priscilla, Songporne Tongruksawattana, and Matin Qaim. 2018. “Synergies between Different Types of Agricultural Technologies in the Kenyan Small Farm Sector.” *The Journal of Development Studies* 54 (11):1974–90. https://doi.org/10.1080/00220388.2017.1342818.

Zhang, Weifeng, Guoxin Cao, Xiaolin Li, Hongyan Zhang, Chong Wang, Quanqing Liu, Xinping Chen, et al. 2016. “Closing Yield Gaps in China by Empowering Smallholder Farmers.” *Nature* 537 (7622). Nature Publishing Group:671–74. https://doi.org/10.1038/nature19368.

APPENDIX

Appendix 1. Hausman test for the estimates of the random effects (RE) and fixed effects (FE) models

Regressors	RE		FE	
	Coef.	s.e.	Coef.	s.e.
t	0,1054***	(0,013)	0,1070***	(0,013)
c	7,5647***	(0,118)	7,5369***	(0,050)
n	235			
R^2	0.0647			
Hausman (RE vs. FE)	1.46 (0.2276)			

Source: survey data;
*** p<0.001; ** p<0.01; * p<0.05; + p<0.10