Agricultural productivity and forest preservation in the Brazilian Amazon

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Abstract:

In recent decades, the northern states of Brazil have experienced high rates of agricultural productivity change and also high rates of deforestation. In this article we examine the impact of the former on the latter. We pose the question whether technical change has been biased toward or against forest preservation – decreasing or increasing the amount of agricultural commodities that must be given up to preserve a unit of forest. Here we estimate the rate and biases of technical change for municipalities in the "arc of deforestation" in the Brazilian Amazon Forest, 2003 to 2015. We represent the production possibility frontier between agriculture and deforestation with a directional distance function with deforestation as an undesirable output. Our results differ by municipality, showing an average annual rate of technical change of 4.9%, and an average bias toward agricultural outputs relative to deforestation, thus reflecting increasing opportunity costs for marginal reductions in deforestation.

Acknowledegment:

JEL Codes: O44, Q15

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ABSTRACT

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Key words: Amazon Forest, Agricultural productivity, Technical Change.

JEL: O44, Q55, Q15.

INTRODUCTION

Brazil encompasses the largest tropical forest in the world, the Amazon forest – corresponding to 13% of the world's forest area and around 60% of Brazil's surface. Strong agricultural expansion, starting in the 1990s, has impacted this area greatly. In the literature, grains, livestock and timber production are indicated as the main drivers of deforestation in the agricultural frontier of this region, referred as the "arc of deforestation" [Riveiro *et al.* (2009); Margulis (2004); and Nepstad *et al.* (2001)]. According to Bragagnolo *et al.* (2010), this region has been experiencing high rates of technical change in agriculture, which they estimate to be 6.7%[1] per year for the period 1975-2006.

Two other studies have investigated the effects of technical change on deforestation in Brazil. Filho *et al.* (2015) show that deforestation control will have small effects on the Brazilian food supply, which could be offset by technological improvements. Villoria *et al.* (2014) do not provide a quantitative analysis but they highlights the role of technical change on forest preservation and stress the need for empirical work to quantify it.

In this article, we estimate the rate of technical change for the "arc of deforestation" in the Brazilian Amazon during 2003-2015, considering deforestation as an undesirable output. Specifically, we measure both the rate of technical change and its effect on the opportunity cost of forest preservation; i.e. whether technical change in agriculture has been biased toward agricultural production or deforestation. To do this we estimate a municipality-level production possibility frontier (PPF) for agriculture for the period 2003 to 2015. This permits us to identify whether technical change was progressive or regressive by analyzing the shift of the PPF, and whether technical change was biased toward or against deforestation.

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[1] This is the average of the technical change rates in Bragagnolo *et al.* (2010) for the states included in our analysis.

Our results indicate that Brazilian agriculture in the “arc of deforestation” experienced progressive technical change at the rate of 4.9% a year. This is an outward shift of the production possibility frontier - a simultaneous expansion of agricultural activities (livestock, timber and grains production) and contraction of deforestation, at an average annual rate of 4.9% . Our estimates of the bias in technical change indicate that innovations in the agricultural sector have been biased against deforestation, i.e., it has become possible to produce more grains and livestock per unit of deforestation. This implies that the opportunity cost of preserving one hectare of forest has increased over time.

BACKGROUND

In the literature, the “arc of deforestation” is defined as the set of municipalities in the agricultural frontier in the northern region of Brazil with high level of deforestation. In this paper, we investigate technical change in agriculture when deforestation is also considered. We use information from 287 municipalities in nine states that have high levels of deforestation[2]: Acre (AC), Amazônia (AM), Roraima (RR), Rondônia (RO), Amapá (AP), Para (PA), Mato Grosso (MT), Tocantins (TO) and Maranhão (MA). Figure 1 illustrates total deforestation during the period from 2001 to 2015 by municipality. For perspective, the 2249 square miles that were logged in the “arc of deforestation” just in 2015 constitute an area slightly larger than the state of Delaware.

[Figure 1]

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[2] We selected 287 municipalities based on the accumulated deforested area in each municipality from 2001 to 2015. The median municipality deforested 13 thousand hectares for the entire period 2001-2015. Our sample consists of municipalities that deforested at least 13 thousand hectares.

Rivero *et al.* (2009) assert that high rates of deforestation between 1995 and 2006 were caused partially by grain and livestock expansion in the North and Midwestern regions. In addition to these two activities, timber revenue is also a motivation for deforestation [Rivero *et al.* (2009); Margulis (2004); Cardille *et al.* (2003); Nepstad *et al.* (2001); Quintanilha and Lee Ho (2005)]. Other studies that highlight the relationship between agriculture and deforestation in Brazil are Reis and Guzmán (1992), Andersen *et al.* (2002), Diaz and Schwartzman (2005), Nepstad *et al.* (2007), Araujo *et al.* (2009), Börner *et al.* (2010), Bowman *et al.* (2012), Assunção *et al.* (2013), and Nepstad *et al.* (2014).

Regarding the role of technical change in forest preservation, Villoria *et al.* (2014) suggest that technical change (and productivity change) could lead to two opposite effects on forest preservation; higher deforestation as commercial activity is expanded, or lower deforestation due to less land intensive production (input substitution). They argue that empirical work is needed to test which of these effects has prevailed.

Filho *et al.* (2015) investigated whether Brazil can increase food supply without increasing deforestation. They assert that conversion of low-yield pasture area can neutralize the effect of reduced deforestation on agricultural supply. To obtain these results, they used a Computable General Equilibrium (CGE) model of Brazil to model land use over 20 years. One of drawbacks of this type of model is the rigidity of the assumptions about the characteristics of agricultural technology (input and output substitution and the relationship to forest area).

There are several studies of productivity of Brazilian agriculture. Bragagnolo *et al.* (2010) estimate Total Factor Productivity (TFP) for Brazilian agriculture using a panel of municipalities and agricultural census data (1975, 1985, 1995 and 2006). They fit a translog production function to obtain the TFP and its several components including technical change. They found an average technical progress of around 3.1%. Using their state-level averages (3.9% in Maranhão to 10.2% in Roraima), we calculate that the simple average technical progress in the states with municipalities in the "arc of deforestation" was around 6.7%.

Gasques and Conceicao (1997), Gasques *et al.* (2004), Gasques *et al.* (2009) and Fuglie (2010) have all previously measured agricultural TFP rates higher than 3% for Brazil. Gasques *et al.* (2014) argue that a favorable international scenario, public research, and credit availability had important roles in these results. Rada and Valdes (2012) also found positive TFP, mainly driven by technical change, at a rate of about 4% for recent decades. Mendes *et al.* (2009) and Trindade and Fulginiti (2015) measured lower TFP growth rates, 1% for 1985-2004 and 2% for 1969-2009, respectively. Gomes and Braga (2008) investigated factors associated with agricultural TFP in the Legal Amazon using state level data. They found that infrastructure and credit made available by a regional institution (Fundo Constitutional de Financiamentos do Norte) contributed to higher TFP rates. None of these studies considered the relationship between agricultural TFP and deforestation.

The harmful environmental effects of the production of *goods* have been studied using directional output distance functions with two kinds of outputs: undesirable (e.g. pollution) and desirable (e.g. *goods*). Chung *et al.* (1997) argue that rates of productivity change estimated using conventional methods that do not consider harmful byproduct effects on the environment are biased. Only a few studies have included undesirable outputs to evaluate productivity change in agriculture, for example, Färe, *et al.* (2006) and Kabata (2011) for the United States and Flavigna, *et al.* (2013) for Italy. In this paper, we estimate the rate and biases of technical change in the Brazilian Amazon "arc of deforestation" when deforestation is included as an undesirable byproduct. We seek to identify the rate of technical change and whether the bias in that technical change has been towards agricultural production or deforestation.

THE MODEL

Several studies have used directional distance functions to represent a technology that includes the joint production of both desirable and undesirable outputs (Chung, *et al.*, 1997; Macpherson, *et al.*, 2010; Färe, *et al.*, 2006). Chung, *et al.* (1997) questioned the adequacy of long-established frameworks that do not consider undesirable outputs when measuring productivity. We utilize here the approach of Färe *et al.* (2006) to represent production technology that involves both desirable and undesirable outputs.

The agricultural production technology uses inputs $\boldsymbol{x} \in \Re_{+}^{K}$ to develop outputs $\boldsymbol{u} \in \Re_{+}^{P}$. Some outputs $\boldsymbol{y} \in \Re_{+}^{M}$, are desirable (such as grain, livestock and timber production), and some outputs $b \in \Re_{+}^{R}$, are undesirable (such as deforestation). The fact that the deforestation activity is associated with grains, livestock and timber production in this region, has led us to treat deforestation as an undesirable output, as opposed to a traditional input. Färe e*t al.* (2005) argue that including undesirable outputs as inputs implies an unbounded output set. In addition, modeling the joint production of desirable and undesirable outputs emphasizes that decreasing the undesirable output requires a reduction in desirable output (Chung et al., 1997). The corresponding mathematical representation of the directional output distance function in this case is given by (where subscripts $k = (1,2, \ldots, N)$ represent observed units and $t = (1,2, \ldots, T)$ for years are dropped for simplicity):

$$\vec{D}_o\left(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}, t; \boldsymbol{g}_{\boldsymbol{y}}, \boldsymbol{g}_{\boldsymbol{b}}\right) = max\left\{\alpha \colon \left(\boldsymbol{y} + \alpha \boldsymbol{g}_{\boldsymbol{y}}, \boldsymbol{b} - \alpha \boldsymbol{g}_{\boldsymbol{b}}\right) \epsilon\, P(\boldsymbol{x})\right\} \qquad (1)$$

which defines a directional distance function for an output possibility set $P(\boldsymbol{x})$, where $\boldsymbol{g_y}$ and $\boldsymbol{g_b}$ constitute the directional vector $\boldsymbol{g} = (\boldsymbol{g_y}, -\boldsymbol{g_b})$. The directional distance function is non-negative in (***y*, *b***), non-increasing and strongly disposable in ***y***, non-decreasing in ***b***, weakly disposable and concave in (***y*, *b***). We impose homogeneity in outputs via the translation property:

$$\vec{D}_o(\boldsymbol{x}, \boldsymbol{y} + \alpha\boldsymbol{g_y}, \boldsymbol{b} - \alpha\boldsymbol{g_b}, t; \boldsymbol{g_y}, -\boldsymbol{g_b}) = \vec{D}_o(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}, t; \boldsymbol{g_y}, -\boldsymbol{g_b}) - \alpha, \quad \alpha \in \Re \tag{1a}$$

which states that increasing desirable outputs by $\alpha\boldsymbol{g_y}$ and simultaneously decreasing undesirable outputs by $-\alpha\boldsymbol{g_b}$ is equivalent to subtracting the translation factor α from the original directional distance function.

Equation (1) is represented in output space in Figure 2 for the case of one desirable output *y* and one undesirable output *b*, and assuming a directional vector $\boldsymbol{g} = (g_y, -g_b) = (1, -1)$. Here, the observation k^t jointly produces in year *t*, one desirable output (*y*) and one undesirable output (*b*), given an input set ($\boldsymbol{x}$). The distance of observation k^t from the frontier is represented as a projection from point A along vector *g* to point B. The directional output distance function measures this distance as α, the maximum feasible simultaneous expansion of *y* and contraction of *b*, with α measured in multiples of the vector $\boldsymbol{g} = (g_y, -g_b)$.

[Figure 2]

The distance of the observation with respect to the contemporaneous frontier, interpreted as inefficiency, is *B – A* for period *t* and *D – C* for period *t +1*. All efficient units are on the frontier, represented by $\vec{D}_o(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}, t; 1, -1) = 0$. For all observations in the output set $\vec{D}_o(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}, t; 1, -1) \geq 0$.

An outward shift of the frontier suggests progressive technical change while an inward shift indicates a regressive technical change. A neutral technical change is implied if the MRT is the same at point B and point D, projections of the original observation to the two frontiers. If the MRT changes, technical change is by definition biased. The technical change has altered the frontier tradeoff (MRT) between good and bad outputs. In the case illustrated in Fig 2, technological change is biased toward *y*, in accord with the Hicksian notion that, if there were no change in prices, producers would respond to the technical change by increasing production of y more than production of b decreases (a point not shown, but northeast of point D, where the tangency has the same slope as at point B). Clearly, it is possible that the shift in the frontier due to technical change may be neutral in some regions, biased in others. We estimate both the average rate and average bias of technical change at each data point, as described below.

Primal output-based directional measure

We evaluate the impact of technical change following the strategy developed by Färe and Karagiannis (2014). The total differential of the distance function is

$$-\left(\nabla_b \vec{D}_o\right)' g_b d\alpha + \left(\nabla_y \vec{D}_o\right)' g_y d\alpha + \frac{\partial \vec{D}_o}{\partial t} dt + \nabla_x \vec{D}_o dx = 0 \tag{2}$$

Specifying $dx = 0$, imposing the translation property[3] and solving for the rate of technical change, $d\alpha/dt$:

$$\frac{d\alpha}{dt} = \frac{\partial \vec{D}_o}{\partial t} \tag{3}$$

Technical change is thus measured as the common number of times the desirable output and the undesirable output vectors (g_y and g_b) can be added to the desirable output and subtracted from

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[3] The translation property implies that the unit will be more efficient by α if an increase in desirable output by α and contraction in undesirable output by α occurs (Färe *et al.*, 2005). Chambers (2002) shows that this can be represented as $-\left(\nabla_b \vec{D}_o\right)' g_b + \left(\nabla_y \vec{D}_o\right)' g_y = -1$.

the undesirable output as a result of technological change. In Figure 2 it is represented by the length of the segment *BD*.

Bias of technical change

There are several ways of investigating technical change biases. Kumar and Managi (2009) use Antle's (1984) dual profit-based multifactor measure of biased technical change. We use a primal definition of bias proposed by Fulginiti (2010), based on Hicksian pair-wise biases of technical change. These are defined as the change in the MRT as a result of technical change along an expansion path for one desirable output *y* and one undesirable output *b*.

$$B_{y,b}(\boldsymbol{y},\boldsymbol{b},\boldsymbol{x},t) \equiv \frac{\partial \ln\left(MRT_{y,b}\right)}{\partial t} \tag{4}$$

where $MRT_{y,b}$ is defined as the ratio of that $\partial\vec{D}_o/\partial b$ and $\partial\vec{D}_o/\partial y$, which are derivatives with respect to outputs which is positive and negative respectively due to monotonicity. $B_{y,b}$ measures the biases in technical change as changes in the slope of the production possibility frontier along an expansion path. $B_{y,b} > 0$ indicates that technical change leads to an increase on the substitution between desirable output *y* and undesirable output *b* is biased towards the production of the desirable output *m* relative to undesirable output *r*. $B_{mr} < 0$ indicates that technical change is biased against production of desirable output *m* relative to undesirable output *r*.

The MRT in this case measures the opportunity cost of decreasing the undesirable output *r* in terms of forgone desirable output *m*. A positive bias implies an increase in this opportunity cost. It can also be interpreted as a decrease in the cost of increasing the desirable output *m* in terms of the undesirable *r*.

THE APPLICATION

Our sample of municipalities from the more than 700 municipalities in the Legal Amazon region was selected based on the accumulated level of deforestation over the period from 2001 to 2015. We first calculated total deforestation over this period per municipality. For example, the municipality of Sao Felix do Xingu, in the state of Para, has deforested one million hectares during the period 2001 to 2015. At the median of the distribution, a municipality deforested thirteen thousand hectares during this period. We selected municipalities that have total deforestation during this period above this median. Thus, our sample consists of municipalities that have deforested more than thirteen thousand hectares during the period 2001-2015. The panel is composed of 287 municipalities during the period 2003-2015.

Data

Descriptive statistics for the variables defined below are presented in Table 1. Data on desirable outputs and inputs, 2003-2015, were obtained from the Brazilian Institute of Geography and Statistics (IBGE, 2017). We obtained information on grains, livestock and timber production, indicated in the literature as the main drivers of deforestation. Grain production is measured as the sum of corn and soybean production (in tons). Timber is measured in cubic meters of logged wood. Livestock production is measured in thousand liters of milk, given that data on cattle sold is not available on an annual basis.

Deforestation, measured in hectares, was obtained from the National Institute for Space Research (INPE/PRODES, 2017). Margulis (2004) suggests that deforestation of a given plot might occur over three years, and be detected only in the third year of the process, depending on the process of deforestation used. It is possible that agricultural activities would be occurring during this process with revenue from both agriculture and timber sales during this period. This leads us to measure deforestation for a given year as the average of the current and previous two years.

Municipalities in the state of Para and Mato Grosso have the largest average deforestation, 6,595 and 5,951 hectares, respectively. Grain production in municipalities in the state of Mato Grosso average 273,037 tons of grains per year. Municipalities in the state of Rondônia have the largest average livestock production, 13,337 thousand liters of milk. Municipalities in the state of Para have the largest average production of timber, 83,972 m^3.

[Table 1]

We were able to obtain information on three inputs, all from IBGE. Labor is represented by population in the municipality. On average, 51% of the municipality's population are in rural areas; less than 25% of these municipalities have rural population less than thirty percent. Agricultural area is measured in hectares, obtained by subtracting forest area from the total area of the municipality. Capital is represented by stock of livestock, in number of head. Following Färe *et al.* (2005), all these variables are normalized by their means[4], aiming to achieve convergence in the stochastic estimation. In addition to these inputs we add a time trend to capture exogenous technical change.

Empirical strategy

We approximate the distance function (Eq. 1) using a quadratic flexible functional form, with the subscript $i = (1,2,\ldots,N)$ representing municipalities and subscript *t* dropped for simplicity

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[4] For a hypothetical municipality that uses mean inputs and produces mean outputs, the input and output variables would be $(x, y, b) = (1,1,-1)$.

$$\vec{D}_{o,i}(x, y, b, ; t, 1, -1) = \gamma_0 + \sum_{k=1}^{3} \gamma_k x_{ki} + \theta_1 b_i + \sum_{m=1}^{3} \beta_m y_m + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3} \gamma_{kl} x_{ki} x_{li}$$

$$+ \frac{1}{2}\sum_{m=1}^{3}\sum_{m'=1}^{3} \beta_{mm'} y_{mi} y_{m'i} + \frac{1}{2}\theta_{11} {b_i}^2 + \sum_{m}^{3}\sum_{k=1}^{3} \delta_{mk} x_{ki} y_{mi} + \sum_{k=1}^{3} \varphi_k x_{ki} b_i \qquad (5)$$

$$+ \sum_{m=1}^{3} \mu_m y_{mi} b_i + \upsilon_1 t + \frac{1}{2}\upsilon_{11} t^2 + \sum_{k=1}^{3} \vartheta_{k1} x_{k,i} t + \sum_{m}^{3} \eta_m y_{mi} t + \lambda_1 t b_i$$

where x_{ki} are labor, capital, and area, y_{mi} are timber, livestock and grains, b_i is deforestation, *t* is technical change measured as year, and γ_0, β's, θ's, δ's, φ's, υ's, ϑ's and μ's are parameters to be estimated. The intercept is a constant term plus municipality fixed effects (dummies). Following Färe *et al.* (2005) we use the directional vector $\boldsymbol{g} = (\boldsymbol{g_y}, -g_b) = (\mathbf{1}, -1)$ representing a simultaneous expansion in desirable outputs and contraction of undesirable output. The symmetry properties in outputs and inputs are imposed before estimation, requiring the following restrictions:

$$\sum_{\mathrm{m}}^{3} \beta_{\mathrm{m}} - \theta_1 = -1; \quad \sum_{\mathrm{m}'=1}^{3} \beta_{\mathrm{mm}'} - \mu_{\mathrm{m}} = 0; \quad \theta_{11} - \sum_{\mathrm{m}=1}^{3} \mu_{\mathrm{m}} = 0; \quad \sum_{\mathrm{m}}^{3} \delta_{\mathrm{mk}} - \varphi_{\mathrm{k}} = 0$$

$$\sum\nolimits_{\mathrm{m}}^{3} \eta_{\mathrm{m}} - \lambda_1 = 0, \ \mathrm{m} = 1, 2 \text{ and } 3; \ \mathrm{k} = 1, 2 \text{ and } 3; \ \beta_{gf} = \beta_{fg}.$$

We estimated equation (5) after imposing the translation property as

$$-\alpha_i = \vec{D}_{o_i}\left(x_i, y_i + \alpha_i, b_i - \alpha_i; 1, -1\right) + \epsilon_i, \qquad (6)$$

where α_i is the translation factor and ϵ_i is error term. The following quadratic flexible functional form with symmetry and translation properties imposed is estimated as

$$
\begin{aligned}
-b_i = {} & \gamma_0 + \sum_{k=1}^{4}\gamma_k x_{ki} + \theta_1 b'_i + \sum_{m=1}^{3}\beta_m y'_m + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3}\gamma_{kl}x_{ki}x_{li} \\
& + \frac{1}{2}\sum_{m=1}^{3}\sum_{m\prime=1}^{3}\beta_{mm\prime}y'_{mi}y'_{m\prime i} + \frac{1}{2}\theta_{11}{b'_j}^{2} + \sum_{m}^{3}\sum_{k=1}^{3}\delta_{mk}x_{ki}y'_{mi} + \sum_{k=1}^{3}\varphi_k x_{ki}b'_i \\
& + \sum_{m=1}^{3}\mu_m y'_{mi}b'_i + \upsilon_1 t + \frac{1}{2}\upsilon_{11}t^2 + \sum_{k=1}^{3}\vartheta_{k1}x_{k,i}t + \sum_{m}^{3}\eta_m y'_{mi}t + \lambda_1 t b'_i + \epsilon_i
\end{aligned}
\tag{7}
$$

where $y'_{1i} = y_{1i} + \alpha_i$, $b'_i = b_i - \alpha_i$. In our case, $\alpha_i = b_i$[5], so the parameters associated with b_i are obtained after estimation using the translation property restrictions. Technical change is estimated following equation (3) as

$$\frac{\partial\vec{D}_o}{\partial t} = \upsilon_1 + \upsilon_{11}t + \sum_{k=1}^{3}\vartheta_{k1}\mathrm{x}_{\mathrm{k,i}} + \sum_{m}^{3}\eta_m y_{mi} + \lambda_1 b_i \tag{8}$$

where λ_1 will be recovered using the restriction imposed by the translation property. Technical change biases are calculated using Equation (4) as

$$B_{y_{mi},b_i}(y_{mi}, b_i, \boldsymbol{x}, t) \equiv \left[\frac{\lambda_1}{\nabla\vec{D}_{b_i}} - \frac{\eta_m}{\nabla\vec{D}_{y_{mi}}}\right] \tag{9}$$

where $\nabla\vec{D}_{b_i}$ and $\nabla\vec{D}_{y_{mi}}$ represent the first derivatives of the directional distance function with respect to the undesirable and desirable outputs, respectively, or

$$\nabla\vec{D}_{b_i} = \theta_1 + \theta_{11}b + \sum_{\mathrm{r}=1}^{3}\varphi_{\mathrm{k}1}\mathrm{x}_{\mathrm{ki}} + \sum_{m=1}^{3}\mu_m y_{mi} + \lambda_1 t \geq 0 \tag{10}$$

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[5] In this paper, we have also estimated Eq. (6) considering $\alpha_i = -y_{1i}$. Results are quite consistent with the model the results from Eq. (7).

$$\nabla \vec{D}_{y_{mi}} = \beta_m + \sum_{m=1}^{3} \beta_{mm'} y_m + \sum_{k=1}^{3} \delta_{k1} x_{ki} + \mu_{m1} b + \eta_m t \leq 0$$

by the monotonicity property, i.e. the directional distance should not decrease with undesirable outputs and not increase with desirable outputs. These properties are checked after estimation.

We first use Corrected Ordinary Least Squares (COLS) to provide starting values of the parameters for the MLE procedure. In the estimation of Equation (7) the composite error term is $\epsilon_i = u_i - z_i$, where u_i represents the standard error term and z_i captures the distance from the frontier. We assume a half-normal distribution for $z_i \sim N^+(0, \sigma_z^2)$ in the MLE, as described in Kumbhakar, Wang, and Horncastle (2015). The estimation was done using Stata 14 following the command *sfmodel* suggested by Kumbhakar, *et al.* (2015) and *sfcross* suggested by Belotti, *et al.* (2012).

RESULTS AND DISCUSSION

We estimated the quadratic specification for the directional distance function in equation (7) using a frontier Maximum Likelihood Estimation (MLE) approach[6]. Parameters estimated are displayed in Table2. The MLE[7] estimation has 30 statistically significant parameters out of 36 (excluding municipality dummies). A Likelihood Ratio test of 35.09 indicates that MLE estimates with a half-normal distribution for the one-sided error term are superior to the COLS estimates (the one percent critical value is 5.4).

[Table 2]

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[6] In the appendix we present parameters estimated by alternative econometric approaches.

[7] The monotonicity property was checked after estimation at each data point; less than 2% of the observations violate monotonicity in grains, around 8% violate it with respect to timber, less than 2% with respect to livestock and less than 4% with respect to deforestation.

An estimate of the distance of each municipality from the frontier is obtained from equation (7), and is interpreted as a measure of inefficiency. The average distance estimated for the region was 0.19. This means that on average, using best demonstrated practices, agricultural outputs (grains, timber and livestock) could be expanded by 19% each while simultaneously decreasing deforestation by 19%.

The estimated rate and biases of technical change vary over the production space, depending on the level of inputs and outputs for individual municipalities at each point in time. We evaluate the estimated rate and biases for each observation in the data set, then calculate an average of all observations. The average rate of technical change estimated for this region during the period 2003-2015 is 4.93%. This means that on average, technical change has allowed municipalities to expand agricultural outputs (grains, timber and livestock) by around 4.93% while simultaneously contracting deforestation by 4.93%. Figure 3 displays the evolution of the average rates of technical change for the "arc of deforestation" when average rates are calculated for individual years.

[Figure 3]

In Figure 4 we present a histogram of the estimated average rates of technical change when calculated at the municipal level, on average, 4.9%. During this period the area deforested declined; twenty five percent of the municipalities decreased deforestation 94% and only three municipalities have higher deforestation in 2015 than in 2003. Municipalities along the southernmost boundary of the "arc of deforestation" (or the outer boundary of the Amazon Forest), where agricultural production has been established for several years, show high rates of technical change (see Figure 5).

[Figure 4]

[Figure 5]

We were interested in measuring not only the rate of technical change, but also whether technical change was biased toward agricultural production and against deforestation, or vice-versa. We evaluate this assertion by estimating how the Marginal Rate of Transformation between agricultural outputs and deforestation changes through time. Our results, as derived below, indicate that municipalities in the “arc of deforestation” have been experiencing technical change that is biased toward agricultural output and against deforestation. That is, on the production possibilities frontier, less deforestation is necessary to increase a unit of agricultural output, or alternatively, more agricultural output must be foregone to reduce a unit of deforestation. This implies that if legal restrictions are expanded to reduce deforestation, the cost in terms of agricultural output given up is now higher.

We evaluate average pairwise technical change biases relative to deforestation using Equation (9), for each subset of desirable outputs. For example, to evaluate whether technical change has been biased toward grains and against deforestation we evaluate Equation (9), B_{y_1,b_1}, at each observation, then calculate the average. We proceed in the same manner to estimate average technical biases with respect to timber and livestock. We find that the average bias for grains relative to deforestation is $B_{y_1,b_1} = 0.12$, for timber relative to deforestation is $B_{y_3,b_1} = 0.14$ and for milk relative to deforestation is $B_{y_2,b_1} = 0.08$. These estimates indicate that, as technical change has taken place, more of these agricultural outputs must be foregone to decrease one hectare of deforestation.

Figure 6 shows that agricultural output has increased, especially grains, while deforestation decreased, consistent with our finding that technical change would have led to increases in agricultural outputs simultaneously with smaller levels of deforestation.

[Figure 6]

We can evaluate the implications of our results for a subset of "priority" municipalities. In 2007, the Brazilian government identified a list of priority municipalities with high levels of deforestation and high rates of growth of agricultural output, where strict monitoring would take place. They are spread in the “arc of deforestation” region[8] but clustered in the states of Para and Mato Grosso. Our results show that the average rate of technical change in the priority municipalities was 10.3%, compared to 3.8% in the others[9]. This result reflects the pressure for forest conversion in those municipalities.

Brazilian policies to control deforestation and to promote agricultural production, such as the 2004 Action Plan for Deforestation Prevention and Control in the Legal Amazon[10], may be related to these results in two ways. First, these programs have focused attention on the tradeoff between deforestation and agricultural production, providing incentives and enforcement to reduce deforestation. This would lead us to observe allocations with less deforestation even at the cost of some reduction in agricultural outputs (corresponding to points A,B,C or D in Figure 2). Second, the policies may have affected the measured shift of the production possibilities frontier, by inducing adoption of innovations that would allow yield increases while reducing deforestation (Nepstad *et al.*, 2014).

Interventions such as the Soy Moratorium (SoyM) in 2006, and the Cattle Agreement in 2010, also constituted obstacles to deforestation despite the fact that they are voluntary and not enforced (Nesptad *et al.*, 2014; Gibbs *et al.*, 2014). The enforcement of new regulations such as

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[8] The 49 priority municipalities chosen by INPE/PRODES are within the sample in this paper.

[9] The null hypothesis of zero difference in these means was rejected at the 1% level.

[10] Plano de Ação para a Prevenção e Controle do Desmatamento na Amazônia Legal – PPCDAm found at http://www.mma.gov.br/florestas/controle-e-preven%C3%A7%C3%A3o-do-desmatamento/plano-de-a%C3%A7%C3%A3o-para-amaz%C3%B4nia-ppcdam

the Brazilian Forest Code (FC), the Rural Environmental Registry of private property (CAR), and surveillance by the Brazilian Institute of the Environment and Renewable Natural Resources (IBAMA), have had positive impacts as deforestation control mechanisms (Gibbs *et al.*, 2014; Soares-Filho *et al.*, 2014; Hargrave and Kis-Katos, 2013). The impact of these regulations on the rate and bias of technical change has not been explicitly studied in this research, but we speculate that the intensification measured by the bias in technical change might have been, in part, a result.

The Brazilian government has also invested in infrastructure, public research and extension, and has promoted agricultural production via increased credit availability (Gomes and Braga (2008); Gasques *et al.* (2014)). From 1999 to 2009, credit availability through the Program to Support Family Farms (PRONAF)[11] has increased yearly at a rate of 23% for the states considered in this paper. The total credit made available by the government to this region was six-fold in 2009 compared to 2001. These incentives would appear to favor increased agricultural production, rather than deforestation, *per se*, contributing to the agricultural production bias that we have measured.

CONCLUSIONS

This article evaluates whether the high rates of technical change reported in the literature for Amazon agriculture persist if deforestation, an undesirable output, is considered in the evaluation. It also examines the nature of the biases in technical change relative to deforestation to determine whether innovation has made it less or more costly to reduce deforestation. Our analysis is based on a sample of 287 municipalities in the “arc of deforestation” in Brazil over

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[11] Programa Nacional de Fortalecimento da Agricultura Familiar

the period 2003-2015. An aggregate municipality-level technology was estimated using a directional distance function with data on grains, livestock and timber production from IBGE and deforested area from INPE. The directional distance function was specified as a flexible quadratic form and estimated using a frontier stochastic approach.

Our results reveal that the rate of technical change (increased agricultural production and decreased deforestation, holding inputs and prices constant) averaged about 4.9% per year during the period from 2003 to 2015. This means that agricultural production and forest preservation have increased during the period of analysis. Our results also indicate that technical change in the has been biased for agricultural production relative to deforestation, requiring increased agricultural production foregone per unit of forest preserved.

The rate of deforestation has been decreasing in Brazil during the period of analysis, while agricultural production has increased. We take this as indirect evidence of the success of Brazilian policies intended to increase agricultural productivity while reducing deforestation. However, news media have reported recently that deforestation in 2016 has been higher than in 2015, the last year of our study. Deforestation in the state of Mato Grosso for example, increased by 190% during the first months of 2016 compared to 2015[12]. This could be evidence of the increased costs we have measured in this analysis. One might also take it as evidence that the REDD+ payments of $5 per hectare preserved are no longer high enough to reduce deforestation, relative to the growing value of agricultural production foregone.

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[12] http://g1.globo.com/mato-grosso/noticia/2016/05/desmatamento-da-amazonia-legal-aumenta-190-em-mt-diz-imazon.html

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Figures and Tables

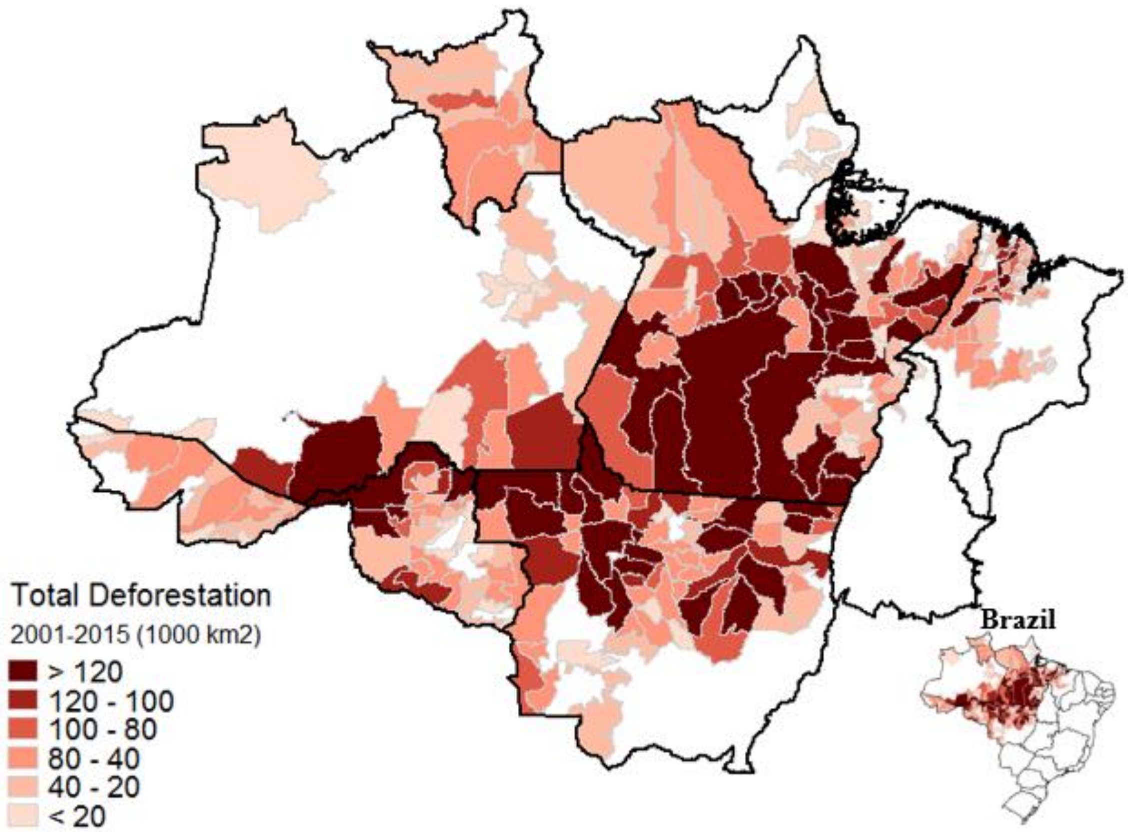

Figure 1. Sum of deforestation (in km^2) for the 287 municipalities in the "arc of deforestation" in the northern region of Brazil.

Note: White are municipalities not included in the estimation of Equation (1). In the application section we describe how we defined the two-hundred municipalities.
Source: Own elaboration using Stata 14.

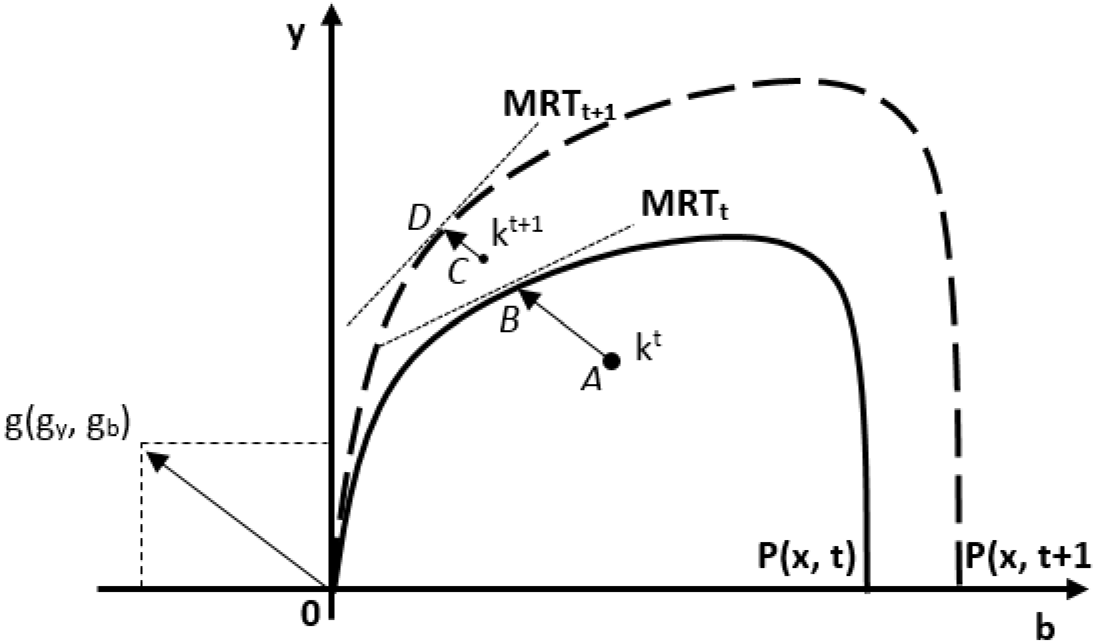

Figure 2. Output Set - *P(x)*, and directional output distance function
Source: Own elaboration.

Table 1. Descriptive Statistics for Agricultural Outputs, Inputs and Deforestation in 287 Municipalities in the Arc of Deforestation, Brazil, 2003-2015.

	Variable	Mean	Standard Deviation	Minimum	Maximum
Outputs					
Average Deforestation (ha)	b_1	4621	8683	0	142463
Grains (tons)	y_1	69112	275835	0	4584870
Livestock (1000 litters)	y_2	5414	8917	0	91953
Timber (m^3)	y_3	40845	114683	0	1521233
Inputs					
Labor (sum of employee)	x_1	43544	126735	1225	2020301
Capital (heads)	x_2	167987	203354	0	2282445
Agricultural area (ha)	x_3	372896	425683	420	7193020

Source: Desirable outputs and inputs were obtained from SIDRA/IBGE and deforestation from INPE/PRODES.

Table 2. MLE Parameter Estimates for Directional Distance Function, municipalities of the arc of deforestation, Brazil, 2003-2015

Coefficient	*Variable*	*Parameter*	*Standard Error*
$\boldsymbol{\beta_1}$	y_1	-0.2418***	(0.0102)
$\boldsymbol{\beta_2}$	y_2	-0.0939***	(0.0065)
$\boldsymbol{\beta_3}$	y_3	-0.5254***	(0.0104)
$\boldsymbol{\beta_{11}}$	y_1^2	0.0022***	(0.0003)
$\boldsymbol{\beta_{22}}$	y_2^2	0.0053***	(0.0004)
$\boldsymbol{\beta_{33}}$	y_3^2	0.0572***	(0.0021)
$\boldsymbol{\beta_{12}}$	y_1y_2	0.0170***	(0.0013)
$\boldsymbol{\beta_{13}}$	y_1y_3	-0.0401***	(0.0015)
$\boldsymbol{\beta_{23}}$	y_2y_3	-0.0150***	(0.0013)
$\boldsymbol{\gamma_1}$	x_1	-0.0156	(0.0466)
$\boldsymbol{\gamma_2}$	x_2	0.3776***	(0.0367)
$\boldsymbol{\gamma_3}$	x_3	0.0069	(0.0256)
$\boldsymbol{\gamma_{11}}$	x_1x_1	0.0019*	(0.0011)
$\boldsymbol{\gamma_{22}}$	x_2x_2	-0.0855***	(0.0147)
$\boldsymbol{\gamma_{33}}$	x_3x_3	0.0002	(0.0026)
$\boldsymbol{\gamma_{12}}$	x_1x_2	-0.0336***	(0.0083)
$\boldsymbol{\gamma_{13}}$	x_1x_3	0.0394***	(0.0116)
$\boldsymbol{\gamma_{23}}$	x_2x_3	-0.0473***	(0.0133)
$\boldsymbol{\delta_{11}}$	y_1x_1	-0.0619***	(0.0038)
$\boldsymbol{\delta_{12}}$	y_1x_2	-0.0328***	(0.0052)

$\boldsymbol{\delta_{13}}$	y_1x_3	0.0401***	(0.0042)
$\boldsymbol{\delta_{21}}$	y_2x_1	-0.0070***	(0.0014)
$\boldsymbol{\delta_{22}}$	y_2x_2	0.0069***	(0.0023)
$\boldsymbol{\delta_{23}}$	y_2x_3	-0.0005	(0.0018)
$\boldsymbol{\delta_{31}}$	y_3x_1	0.0580***	(0.0042)
$\boldsymbol{\delta_{32}}$	y_3x_2	0.0090*	(0.0054)
$\boldsymbol{\delta_{33}}$	y_3x_3	-0.0388***	(0.0057)
$\boldsymbol{\upsilon_{1}}$	t	0.0016	(0.0054)
$\boldsymbol{\upsilon_{11}}$	t^2	0.0011*	(0.0007)
$\boldsymbol{\vartheta_{11}}$	x_1t	-0.0022***	(0.0009)
$\boldsymbol{\vartheta_{21}}$	x_2t	0.0103***	(0.0017)
$\boldsymbol{\vartheta_{31}}$	x_3t	-0.0025*	(0.0014)
$\boldsymbol{\eta_{11}}$	y_1t	0.0112***	(0.0006)
$\boldsymbol{\eta_{21}}$	y_2t	0.0023***	(0.0005)
$\boldsymbol{\eta_{31}}$	y_3t	0.0035***	(0.0009)
$\boldsymbol{\gamma_{0}}$	*Constant*	-0.0774	(0.0899)
$\boldsymbol{\sigma_{u}}$		-2.7958***	(0.1457)
$\boldsymbol{\sigma_{v}}$		-3.5791***	(0.1033)
$\boldsymbol{\lambda_{MLE}}$		1.4794***	(0.0262)

Note: COLS parameters used as starting values for MLE. Standard error in parenthesis; *** for p-value smaller than 0.01, ** smaller than 0.05, and * smaller than 0.1. The dependent variable is the negative of average deforestation. $\boldsymbol{\lambda_{MLE}}$ refers to the estimated $\boldsymbol{\sigma_u/\sigma_v}$ instead of the parameter associated with the interaction between undesirable output and time trend (Eq. 7). It includes 287 municipality dummies. Parameters for deforestation, are recover using the translation property. 3731 observations were used in this regression.

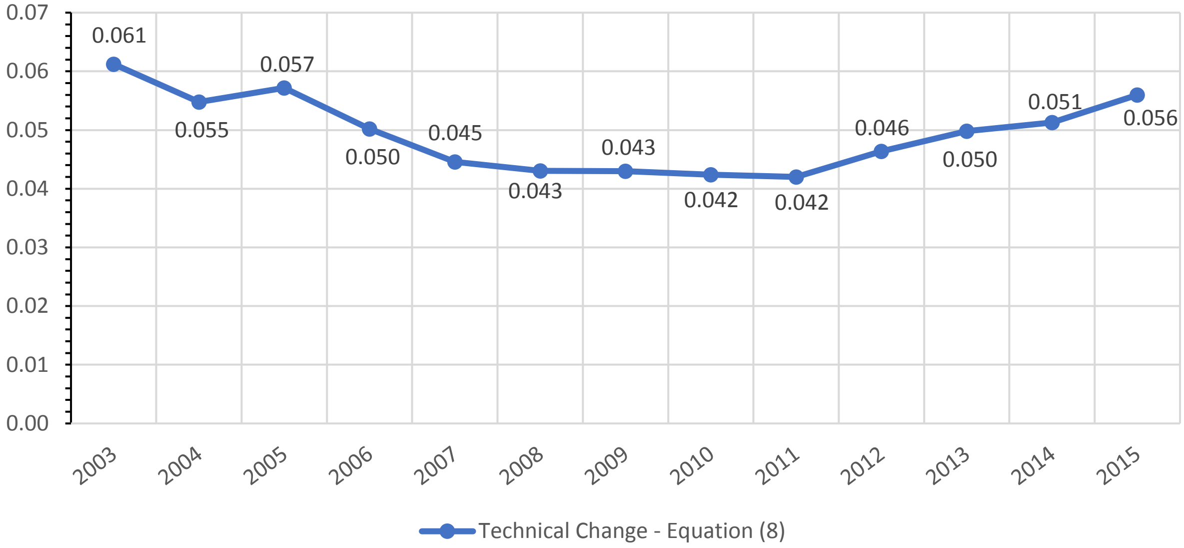

Figure 3. Average technical change rates in the arc of deforestation, Brazil, from 2003 to 2015.

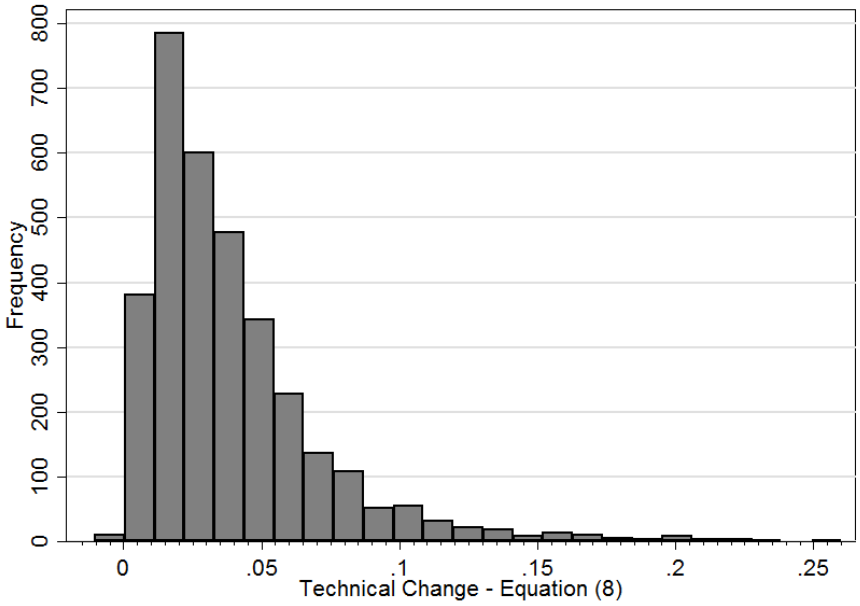

Figure 4. Histogram of average rates of technical change by municipality in the arc of deforestation, Brazil, 2003 to 2015.

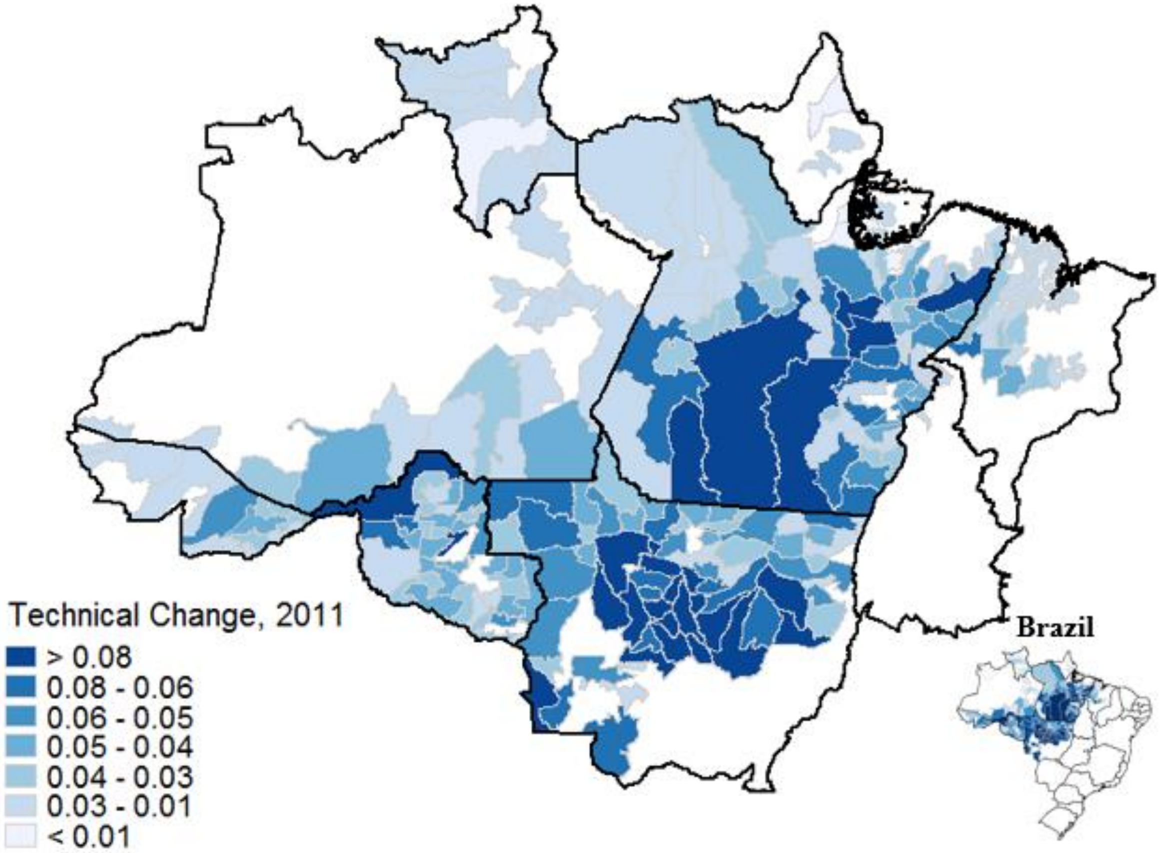

Figure 5. Average rate of technical change by municipalities in the arc of deforestation, Brazil, in 2011.

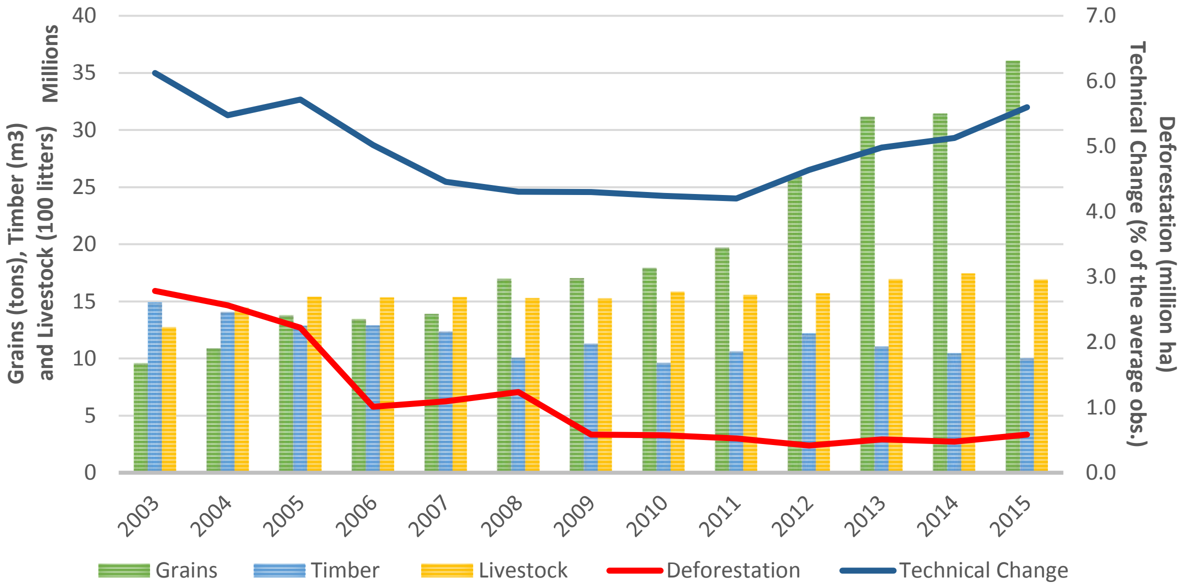

Figure 6 – Evolution of agricultural output, deforestation and the average rate of technical change for the arc of deforestation, Brazil, 2003-2015.

Note: Grains (in tons), timber (in m^3) and milk (in 100 liters) on vertical axis at left while deforestation (in million hectares) and technical change (in percentage) on vertical axis at right.