Did technical change in agricultural production decrease the emission of pollutants on the Amazon Forest during 1990-2009?

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ABSTRACT

The *Amazon Forest* is the largest tropical forest in the world stretching over nine states in northern Brazil. Land use in the *Amazon Forest* has been under discussion due to its direct and indirect effects on emission and sequestration of greenhouse gases (GHGs) such as CO_2, N_2O and CH_4. Our interest here is to investigate whether technological change in agriculture has resulted in higher or lower costs of emissions abatement. We examined a panel of nine states from this region during the period 1990-2009, a period of rapid agricultural expansion as well as a series of new environmental regulations. The rate of technical change and its biases were estimated using stochastic and non-stochastic approaches. Preliminary results indicate a technological progress for Brazilian's Amazon Forest states, which suggests a simultaneously expansion on GDP and contracted on CO_2e emissions due to technical change. This technical change has been biased toward GDP and against emissions, indicating an increase in GDP foregone to achieve a given reduction in emissions.

Key words: Amazon forest, Agriculture, Greenhouse gasses and Technical change.
JEL: Q54, Q55, O13, D24.

1. Introduction

The *Amazon Forest* is the largest tropical forest in the world. Around 60% of Brazil's area, it covers 771 municipios in nine northern states. Its preservation has been the focus of several institutions across the world such as REDD+(Reducing Emission from Deforestation and Forest Degradation), now the Global Climate Fund, and the *United Nations* (UN), *Conference of Parties* (COP) as evidenced in COP21 in Paris last November.

One of the reasons land use in the *Amazon* region have been under scrutiny is the rather important impact it has on atmospheric Carbon Dioxide (CO_2) cycle. Land clearing for commercial agriculture increases pollutants' emission and decreases their sequestration. Agriculture is the main driver of land use change in this region, and responsible for emission of harmful pollutants to human health such as Methane (CH_4) and Nitrous Oxide (N_2O). In 2014, the largest emitters in Brazil were the state of Para, followed by the states of Minas Gerais and Mato Grosso (System Study Greenhouse Gas Emission Estimates – SEEG, 2015).

During the last two decades, technical and efficiency improvements have affected agricultural production in this area and might have affected emissions too. It would be important to know if environmental efficiency has improved or deteriorated. A few studies have looked at technical change in Brazilian agriculture (overall) and in particular in this region [Gomes and Braga (2008), Bragagnolo et al. (2010), and Rada and Valdes (2012)]. They have found technical progress in agriculture. None of the studies have considered pollutants.

This paper aims at investigating the impact of technical change and emissions in agriculture in the Brazilian Amazon states during1990-2009. The objective is to find out if emissions intensity has improved or deteriorated as innovations in agriculture have taken place. CO_2, CH_4 and N_2O are considered. We are not aware of any other study that investigate the nature of technical change in Brazilian agriculture with a focus on the intensity of emissions. We estimate emissions reducing technical progress in the states that represent the agricultural frontier, in particular during 2005-2009.

Section 2 presents a brief description of the Amazon Forest region and the literature that has discussed it. Section 3 illustrates the theoretical framework adopted. It is follow by data description and the empirical specification. Section 5 discusses the results. Section 6 concludes.

2. The Amazon Forest Region

Several studies have investigated the relationship between deforestation and agricultural production on this region (Cattaneo (2002), Morton et al. (2006), Rivero et al. (2009), Richards et. al. (2012), Hargrave and Kis-Kato (2013), Richards et al. (2014), and Araujo et al. (2014)) These studies mainly found that livestock and grains production are the major drivers of deforestation.

Few studies focused on CO_2 emission from land use in this region aiming to evaluate the role of Brazil's participation in REDD+[1]. Nepstad et al. (2007) estimated a cost of US$5.5 per ton carbon if the forest were conserved over 30 years (a total cost of US$ 257 billion). Boner et al. (2010) also found similar results. They conclude that it would be feasible to compensate producers given that the converted land in the Amazon has a low return per hectare. Soares-Filho et al. (2006), also interested in forest conservation, found that at the 2006 deforestation rate, only 60% of the Brazilian Amazon forest would remain by 2050.

Institutional changes and governmental policies and regulations that affect the rate of deforestation have also been the subject of study by Nepstad et al. (2014), Soares-Filho et al. (2014), Nepstad et al. (2013), Stickler et al. (2013), Garret et al. (2013) and Gibbs et al. (2015). Oliveira (2008), Araujo et al. (2009) and Araujo et al. (2010) investigate the strength and characteristics of property rights and found a positive impact of weak property rights on deforestation. Villoria et al. (2014) presents a vast literature review on the impacts of technological change on deforestation. They point out that the relationship between technical progress and deforestation is weak, that global agricultural progress is land saving but that low-yield land abundant regions will experience expansion in the future.

Technical change, or an increase in output per unit of input has been the object of study of many authors, among then Solow (1957), and Griliches (1958). A few studies such as Christensen, Jorgenson, and Lau (1973), Lim and Shumway (1997), Fulginiti (2010) and Färe and Karagiannis (2014) should be highlight by its investigation of the theme and for developing new concepts to also analyze agricultural markets.

Brazilian agriculture has experienced rapid technical progress since the late 70's (Arnade, 1992), with different rates across regions. For instance, Bragnolo et al. (2010) found different rates of technical progress[2] per state for the period from 1975 to 2006, ranging from 10.2% for the state of Amazonia to 1.3% for the Federal District (Brasilia), an average of 4.3% for the whole country. Rada and Valdes (2012) estimated an annual rate of technical change for livestock of 7.13% and for crops of 2.93% during the 1985-2006 period. Helfand et al. (2015) recently have studied the impact of farm size on Total Factor Productivity for Brazilian agriculture. They had access to a

[1] May et al. (2011) and Heres et al. (2013) also discuss the role of REDD+ policies on Brazil.
[2] Arnade (1992) also shows progressive technical change for Brazil during the period 1968-1987, but with rates lower than 1%. In addition, Mendes et al. (2009) estimated the total factor productivity (TFP) for Brazilian agriculture, with average rate of 1.03% for the period of 1985-2004.

unique dataset which consists of representative farms for three different Agricultural Census (1985, 1995/96 and 2005). The authors found a rate of technical change of 5% for Brazil and of 7.09% for the Northern region, on average.

Northern Brazil experienced rapid growth of commercial agriculture after the expansion of grain and livestock production toward the Central-West region – Mato Grosso – during the 90's (Nepstad et al., 2014). Garret et al. (2013) suggest that this expansion has been a main source of deforestation. Total factor productivity growth rates for the Brazilian Amazon region for the period 1990-2004 were estimated by Gomes and Braga (2008). They found an average growth rate of productivity of 2% for the period, with a rate of 2.63% over the 1990-1996 subperiod. They estimated an annual rate smaller than 1% before 1995 and higher than 1% after. The authors suggested that this increase in growth rate is due to changes in the energy sector impacting agriculture and increasing infrastructure in the region.

3. Theoretical framework

The production technology that involves both desirable and undesirable outputs is describe in Färe et al. (2005), Cuesta et al. (2009) and Macpherson et al. (2010) and will be summarized here. The agriculture production technology uses inputs $x_i = (x_{1i}, \dots, x_{Ki}) \in \Re_+^K$ to develop outputs $u_i = (u_{1i}, \dots, u_{Vi}) \in \Re_+^P$. Some outputs are desirable $y_i = (y_{1i}, \dots, y_{Mi}) \in \Re_+^M$, such as the agricultural *Gross Domestic Product* and some undesirable $b_i = (b_{1i}, \dots, b_{Ri}) \in \Re_+^R$, such as CO_2, CH_4 and N_2O emissions. The subscript $i = (1,2, \dots, N)$ represents the observed unit. The production technology is represented in Figure 1, where the output set considered is based on Färe et al. (2005).

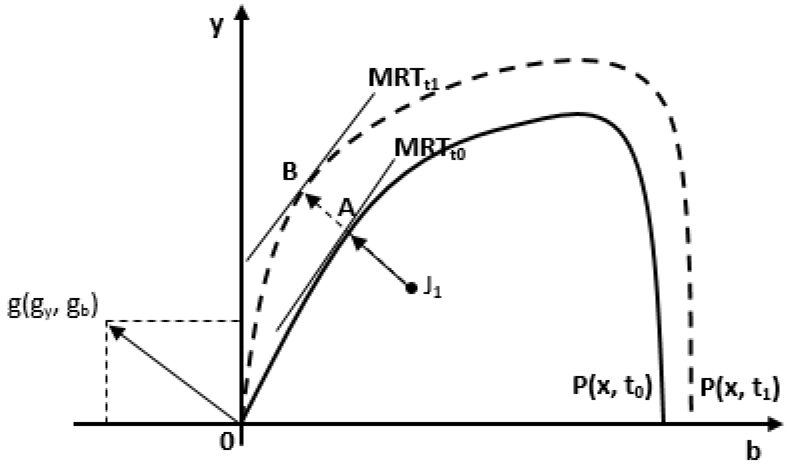

Figure 1: Output Set - *P(x)*, and directional output distance function
Source: Own elaboration.

In the Figure 1, the observation J_1 jointly produces desirable (*y*) and undesirable (*b*) outputs given an input set (*x*). The directional output distance function seeks to maximize the simultaneous expansion of *y* and contraction of *b*. The distance, also known as the inefficiency, is the distance from the frontier (efficient units have a distance equal to zero), given by A – J_1. The mathematical representation of the directional output distance function is given by

$$\vec{D}_o(x, y, b, t; 1, -1) = max\{\alpha: (y + \alpha g_y, b - \alpha g_b) \epsilon P(x)\} \tag{1}$$

defines a directional output distance function. $P(x)$ is the output set, g_y and g_b are elements of the directional vector $g = (g_y, -g_b)$ defined in output space. As in Färe et al. (2005), we assume these to be equal to 1 and -1, respectively, representing an increase of desirable outputs and a reduction of undesirable outputs that occurs simultaneously and proportionally. We are also interested in find out the effect of technical change on the output set, including y and *b*. Technical change is represented by *t* in equation (1) and it is the difference between the two output sets, B - A. The joint-production technology is assumed to be null-joint in desirable and undesirable outputs and weakly disposable in both types of outputs. In other words, production of desirable outputs is possible only under undesirable outputs generation. The directional output distance function is strongly disposable in desirable outputs, non-increasing in desirable outputs, non-decreasing in undesirable outputs, weakly disposable in both desirable and undesirable outputs, and concave in both types of outputs (Färe et al. 2005).

The distance function can be used as measure of efficiency. It takes a value of zero for efficient firms, those on the isoquant of the production set. It is greater than zero for the inefficient firms, those in the interior of the set. We evaluate the impact of technical change following the strategy developed by Färe and Karagiannis (2014). Studies by Weber and Xia (2011) and Badau (2014) have applied these concepts. Following Färe and Karagiannis (2014) the total differential of the distance function is

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

Given the definition of technical change $dx = 0$, then solving for technical change

$$\left[\left(\nabla_b \vec{D}_o\right)' g_b - \left(\nabla_y \vec{D}_o\right)' g_y\right] \frac{d\alpha}{dt} = \frac{\partial \vec{D}_o}{\partial t} \tag{3}$$

and using the translation property[3] it is possible to obtain the rate of technical change as

$$\frac{d\alpha}{dt} = \frac{\partial \vec{D}_o}{\partial t} \tag{4}$$

Färe and Karagiannis (2014) define technical change 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 the undesirable output as a result of technological change. In the Figure 1 it is represented by the length of the segment AB. Equation (4) is the *primal output-based* directional measure of the rate of technical change.

[3]Translation property implies that the unit will be more efficient by α if an increase on 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 $-\left(\nabla_b \vec{D}_o\right)' g_b + \left(\nabla_y \vec{D}_o\right)' g_y = -1$.

We define the *Marginal Rate of Transformation* (MRT) as the boundary of the production possibility set, or output set. In which, following Färe et al. (2005) and using the duality between directional distance function and the normalized revenue function,

$$R(x,p,q) = max_{y,b}\{py - qb : D_O(x,y,b,t) \geq 0\} \tag{5}$$

where $R(x,p,q)$ refers to the normalized revenue function, and p and q are the desirable and output price, respectively. The first order condition is given by

$$\begin{aligned} \nabla_b \overrightarrow{D_O}(x,y,b;g)(pg_y + qg_b) &= q \geq 0 \\ \nabla_y \overrightarrow{D_O}(x,y,b;g)\left(pg_y + qg_b\right) &= -p \leq 0 \end{aligned} \tag{6}$$

Färe et al. (2005) argues that if the observation is efficient ($D_O(x,y,b,t) = 0$) the shadow price ratio ($-q/p$) will be independent of the directional vector. Thus, the ratio of shadow[4] prices is equal to the boundary of the output set:

$$\frac{q_j}{p_m} = -\left[\frac{\partial D_O(x,y,b,g)/\partial b_j}{\partial D_O(x,y,b,g)/\partial y_m}\right], \qquad m = 1,\dots,M \; and \; j = 1,\dots,J \tag{7}$$

where q_j represents the (shadow) price of undesirable output, p_m represents the known price of desirable output, and the right hand side of this expression is the slope of the output set boundary, which is known as MRT. The shadow price of the undesirable output is equal to the normalized price of the desirable output:

$$q_j = -p_m\left[\frac{\partial D_O(x,y,b,g)/\partial b_j}{\partial D_O(x,y,b,g)/\partial y_m}\right], \qquad m = 1,\dots,M \; and \; j = 1,\dots,J \tag{8}$$

As the price of the desirable output is a market price, it is used along with the estimated MRT to calculate the price of the undesirable output. Equation (8) is interpreted as how much of desirable

[4] Shadow because it considers a price vector normalized by the directional vectors and a price of non-market output.

output has to be foregone to decrease one unit of undesirable output. Since, it is a static model, this revenue would have to be foregone annually.

In order to estimate the *Hicksian* and the *Overall Biases* of technical change we follow Fulginiti (2010) and define Hicksian neutrality as the invariance of the MRT along an expansion path. Hicks' biases are:

$$B_{mj}(y,b,x,t) \equiv \frac{\partial \ln\left(MRT_{mj}\right)}{\partial t} = \frac{\partial \ln\left(\nabla_{mt}\vec{D}_o / \nabla_{jt}\vec{D}_o\right)}{\partial t}, m,j = 1,\ldots,M, m \neq j \tag{9}$$

which, according to Fulginiti (2010), can be interpreted as the relative cost of producing additional units of output *m* (CO_2 for example) in terms of units of output *j (GDP* for example). It measures the biases in technical change as a rotation on the *Production Possibility Frontier* (PPF) in output space (Fulginiti, 2010). $B_{mj} > 0$ means that technical change is biased towards the production of output *j* relative to output *m* and $B_{mj} < 0$ indicates the opposite. This bias measure aims to find whether the MRTs displayed in Figure 1 are different due to technical change.

We define the *overall bias* as in Fulginiti (2010),

$$B_{mj}(y,b,x,t) \equiv \sum_{j \neq m=1}^{M} S_{jt}^{v} B_{mj}(y,b,x,t) \qquad , S_{jt}^{v} = \frac{(\nabla_{jt}\vec{D}_o) y_j}{\vec{D}_o} \tag{10}$$

where $, S_{jt}^{v}$ is referred as shadow price of the output *j* (Fulginiti, 2010). $B_{mj} > 0$ means that technical change is output-*m* reducing; $B_{mj} = 0$, it means that the technical change was *Hicks* neutral; and $B_{mj} < 0$, it means that less input is required to produce output *m* relative to the other outputs (output-*m* augmenting).

4. Data and empirical estimation

4.1.Data

Dataset consist of nine states, Amapá, Acre, Amazonas, Mato Grosso, Maranhão, Tocantins, Para, Rondônia and Roraima, and 20 years – from 1990 to 2009. We have one desirable output, agricultural *Gross Domestic Product*, and four undesirable outputs – CO_2, CO_2equivalent, CH_4 and N_2O.

The agricultural sector has increased considerably in the last 20 years, doubling its *Gross Domestic Product* (GDP). This variable was obtained from the Institute for Applied Economic Research (IPEA) website and is illustrated in Figure 2. Mato Grosso's GDP has increased over the period, which indicates an expansion of agriculture to the Central-West region. Additionally, Maranhão, Para and Tocantins have also been important agricultural producers. Para's agricultural activities have decreased by more than 60% during the period.

[Figure 2]

We find different measures of emission in the literature. For instance, Aguiar et al. (2012) have developed a spatial analysis of emission of CO_2, CH_4 and N_2O at a *25 x 25km²* grid, for a short period that has not been aggregated to the state level. The Brazilian Ministry of Science, Technology and Innovation (MCTI) has a panel data set available for a longer time series. The document [5] classifies emission in raw, removal and net emissions. Only net emissions are available in a longer time series at the state level. Since our model is static and considers yearly agricultural production and use of inputs, annual raw emissions from agricultural production would be preferred. We use the emissions data from the System Study of Greenhouse Gas Emission Estimates (SEEG), which uses the MCTI documents (inventories) to estimate the state level raw emission of CO_2, CO_2equivalent, CH_4 and N_2O, among other gases. Figure 3 illustrates CO_2 emission over the period of study for selected states.

[Figure 3]

The states of Mato Grosso and Para have higher CO_2 emissions given the rate of deforestation and the importance of agriculture in the region (Figure A1 and A2). These states also have the highest level of infrastructure, kilometers of pavement roads, in the region, as seen in Figure A3.

[5] Annual Estimates of Greenhouse Gases Emission for Brazil, 2nd edition.

Of interest in this study is emissions of CO_2equivalent (CO_2e GWP[6]) as it is a measure of joint greenhouse gases. Graphically, CO_2e and CO_2 have the same evolution although the former has higher values. CO_2e, estimated by SEEG considers ten different gases (CO_2, CH_4, N_20, HFC-125, HFC-134a, HFC-143a, HFC-152a, CF_4, C_2F_6, and SF_6).

Emission of CH_4 and N_2O are from land use change and from agriculture. This includes emission from forest fires and agriculture production.

[Figure 4]

[Figure 5]

After 2001 Mato Grosso has the biggest share of agricultural among the states considered (Figure 1) but this leadership also produces two major pollutants, CH_4 and N_2O, as illustrated in Figures (4) and (5). In 2009, Mato Grosso was responsible for 40% of the corn produced on the region and more than 90% of soybeans while, in 1990, it produced less than 5% and 35%, respectively (Brazilian Institute of Geography and Statistics – IBGE, 2015). Mato Grosso share of cattle production did not change over the 20 years, keeping around 35%. Rondônia increased its livestock share from 6.5% to 15.4%; Pará kept it constant at 23%, and Maranhão and Tocantins, together, lost 10% of their share (IBGE, 2015).

Galford et al. (2013) points out the fast expansion in corn a soybean in Mato Grosso, also allowed by double-cropping, as one of the reasons for the high emission of N_2O due to nitrogen fertilizer and CO_2 from tillage of the soil. MCTI's inventory indicates manure (residues from cattle) as the main direct and indirect source of N_2O emission at around 60% of the total emissions in 2005.

Figure (6) and Figure (2A) (appendix) show a link between pollutants' emission and agricultural *Gross Domestic Product*. As the agricultural sector expands (contract) emission of CH_4 and N_2O clearly increases (decreases). A clear positive link between CO_2 and agricultural GDP does not exist after 2005 since deforestation has been decreasing due to institutional policies. Nesptad et al. (2014) show evidence of decreasing deforestation (Figure A1) due to law enforcement with the creation of *Detection of Deforestation in Real Time* (DETER) and of the

[6] GWP is Global Warming Potential. It considers the influence of gases in changing earth's energy balance (SEEG, 2015)

Plan for the Protection and Control of Deforestation in the Amazon (PPCDAm), and the occurrence of *Soy Moratorium* in 2006. In fact, although the agricultural sector continues to expand after 2004, CO_2 emissions start to decrease.

[Figure 6]

We constructed two input variables, labor and capital. The former consists on hired labor at agricultural production level, and we obtained at General Record of Employed and Unemployed Workers (CAGED, 2012). Figure 7 displays hired labor over the period for selected states. It illustrates the increasing importance of Mato Grosso, followed by Pará, Maranhão and Tocantins. As mentioned before, the production of grains and livestock increased in these states during this period.

[Figure 7]

Pará has shown a sharp decrease on *GDP* jointly to an increase on hired labor while Mato Grosso has shown an increase in both *GDP* and hired labor. Deforestation, CO_2 emissions and GDP patterns (displayed on Figure A1, Figure 2 and Figure 3) indicate, for the state of Para for example, a dependence of GPD on illegal deforestation.

Capital is modeled by year and state as agricultural real capital stock using the procedure suggested by Mendes et al. (2009) and Gomes and Braga (2008)

$$K_{i,t} = \left[RK_t\left(\frac{GDP_t^{AG}}{GDP_t^{TOT}}\right)\right]x\left(\frac{AgL_{i,t}}{AgL_t}\right), \qquad i = 1, \ldots, 9\ and\ t = 1990, .., 2009; \tag{11}$$

where the subscripts *i* and *t* represents state and year ($K_{i,t}$ is the agricultural real capital stock for state *i* in time *t*), RK_t is the Brazilian real capital stock over the period, GDP_t^{AG} is the Brazilian agricultural *GDP* over the period, GDP_t^{TOT} is the Brazilian total *GDP* over the period, $AgL_{i,t}$ is the land used in agriculture in the state *i* and year *t*, and AgL_t is the land used in agriculture in Brazil. Figure 8 shows the behavior of this variable for selected states.

[Figure 8]

Figure 8 shows the relevance of Mato Grosso on the modern agricultural sector in the region. A trend was used to capture technical change. We also include fixed effects by state. Table 1 has descriptive statistics for all variables.

[Table 1]

4.2.Estimation

Several functional forms have been used to approximate distance functions with undesirable outputs such as the translog (Cuesta et al., (2009), Emvalomatis et al. (2011), Lee et al. (2012), Bukusheva and Kumbhakar (2014), and Zhou et al. (2015)[7]). The quadratic flexible functional form has alse been used (Färe et al. (2005), Färe et al. (2006), Kumar and Managi (2011), Färe et al. (2012), Wei et. al. (2013) and Kumar et al. (2014)) and is preferred over the translog due to the additive nature of the directional distance function. We use the quadratic function to approximate the directional output distance function we use in this study.

Following Färe et al (2005) we use a direction vector $g = (g_y, -g_b) = (1, -1)$ representing a simultaneous expansion of desirable outputs and contraction of undesirable outputs. Thus, we approximate Equation (1) by the quadratic directional distance function

$$
\begin{aligned}
\vec{D}_{o,i}(x, y, b; 1, -1) = {} & \gamma_0 + \sum_{k=1}^{K} \gamma_k x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \gamma_{kl} x_{ki} x_{li} + \sum_{m=1}^{M} \beta_m y \\
& + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} y_{mi} y_{ni} + \theta_r b_{ri} + \frac{1}{2}\sum_{j=1}^{R}\sum_{i=1}^{G} \theta_{rr} b'_{rj} b'_{gi} + \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} x_{ki} y_{mi} \\
& + \sum_{k=1}^{K}\sum_{r=1}^{R} \varphi_{kr} x_{ki} b_{ri} + \sum_{m=1}^{M}\sum_{r=1}^{R} \mu_{mr} y_{mi} b_{ri} + \upsilon_1 t_i + \frac{1}{2}\upsilon_{11} t_i t_i \\
& + \sum_{k=2}^{K+1} \upsilon_{1k} x_{k-1,i} t_i + \sum_{m=1}^{M} \eta_{1h} y_{mi} t_i + \sum_{r=1}^{R} \lambda_{1r} t_i b_{ri}, \; (i = 1,2, \ldots, N)
\end{aligned}
\tag{12}
$$

[7] Zhou et al. (2014) presents a literature review about estimating shadow prices of undesirable outputs.

where y_{mi} is the desirable output represented by agricultural *GDP* for each state *i*, time *t* is not represented in this formulation for simplicity, b_{ri} is the undesirable output represented by the emissions of CO_2, CO_2e, CH4, and N_2O, and x_{ki} represent the inputs used in production, capital and labor. Technical change in this equation is represented by a trend *t*. Dummies are included to account for unobserved characteristics of each state not captured by this model.

Two theoretical properties were imposed on estimation of Equation (12), the translation property and symmetry[8],

$$
\begin{aligned}
-y_{1i} = {} & \gamma_0 + \sum_{k=1}^{3}\gamma_k x_{ki} + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3}\gamma_{kl}x_{ki}x_{li} + \sum_{m=1}^{3}\theta_m b'_{mi} + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=3}^{3}\theta_{mn}b'_m b'_n \\
& + \sum_{n=1}^{3}\sum_{k=1}^{3}\varphi_{k1}x_k b'_n + \upsilon_1 t_i + \frac{1}{2}\upsilon_{11}t_i t_i + \sum_{k=2}^{4}\upsilon_{1k}x_{k-1,i}t_i + \sum_{r=1}^{3}\lambda_{1r}t_i b'_r + \epsilon_i
\end{aligned}
\tag{13}
$$

where γ_0 represents a constant and the state fixed effects. All the variables (*y, b, x*) were normalized by their overall means, and b'_{mi} represent the undesirable output normalized by the output translation factor ($b'_{mi} = b_{mi} - \alpha$), as in equation (1). For equation (13) the agricultural GDP was used as the normalizing factor (α), which by the translation property becomes the dependent variable. Equation (13) was estimated using a distribution-free approach for the inefficiency term, *Ordinary Least Squares* (OLS) where the inefficiencies are calculated by modifications in the error term. This method is known as Corrected OLS (COLS). Kunbhakar et al. (2015) illustrates using a deterministic production frontier represented by

$$
y_i = f(x_i, \beta) - u_i, \quad u_i \geq 0 \tag{14}
$$

where $f(x_i, \beta) = y_i^*$ is the frontier output level, which depends on inputs, x_i, and the parameters estimated, β, and u_i is the production inefficiency. Using a linear functional form, we can re-arrange equation (14) as

[8] These properties are described in the equation (18vii) and (18viii).

$$y_i = \beta_0 + x_i'\tilde{\beta} - u_i \tag{15}$$

which can be estimated by adding a stochastic error, v_i, and using OLS. Since $\epsilon_i = -u_i + v_i$ and $E(u_i) \neq 0$, the intercept, β_0, is biased although the slope coefficients, $\tilde{\beta}$, are not. With the coefficients obtained it is possible to estimate the residuals, $\widehat{\epsilon_i}$, by taking the difference between observable output, y_i, and estimated output, $\beta_0 + x_i'\tilde{\beta}$.

Technical inefficiencies (distance) can be estimate as in Atkinson et al. (2003) and in Badau (2014), recovering the residuals from the OLS regression of equation (13) and performing the following estimation

$$\widehat{\epsilon_i} = f(z_i) + \tau_i \tag{16}$$

where z_i is a vector of variables that might affect the residuals such as state level dummies, interaction with the trend, and socio-economic variables like roads (in kilometers), legal (juridical) expenses, number of conflicts, rate of homicides, and homicides caused by land conflicts; and τ_i is a random error. Equation (16) was estimated using OLS. Technical inefficiency can be captured by subtracting the $\min\{\widehat{\widehat{\epsilon_i}}\}$[9] from the fitted values, $\widehat{\widehat{\epsilon_i}}$ (Badau, 2014).

$$\vec{D}_o(x, y, b; 1, -1) = Technical\ Inefficiencies = \widehat{\widehat{\epsilon_i}} - \min\{\widehat{\widehat{\epsilon_i}}\} \tag{17}$$

For cross-sections, the COLS approach has the drawback that the statistical errors from the frontier cannot be separated from the inefficiencies (Kumbhakar et al., 2015). A second estimation approach was used. The directional output distance function was also estimated using nonlinear programming, following Färe et al. (2005) and Färe et al. (2006).

$$\min \sum_{k=1}^{K} (\vec{D}_o(x^k, \widehat{y^k, b^k}; 1, -1) - 0) \tag{18}$$

$$\text{Subject to} \quad \vec{D}_o(x^k, y^k, b^k; 1, -1) \geq 0, \qquad \text{(i)}$$

[9] The $\min\{\widehat{\widehat{\epsilon_i}}\}$ represents the most technical efficient state since u_i is the smallest (Badau, 2014).

$$\overrightarrow{\partial D}_o(x^k, y^k, b^k; 1, -1)/\partial b \geq 0, \tag{ii}$$

$$\overrightarrow{\partial D}_o(x^k, y^k, b^k; 1, -1)/\partial y \leq 0, \tag{iii}$$

$$\overrightarrow{\partial D}_o(x^k, y^k, b^k; 1, -1)/\partial x \geq 0, \tag{iv}$$

$$\overrightarrow{\partial^2 D}_o(x^k, y^k, b^k; 1, -1)/\partial^2 y = \overrightarrow{\partial^2 D}_o(x^k, y^k, b^k; 1, -1)/\partial^2 b \leq 0, \tag{v}$$

$$\vec{D}_o(x^k, y^k, 0; 1, -1) < 0 \tag{vi}$$

$$\begin{gathered} \beta_m - \sum_{r=1}^{3} \theta_r = -1, \qquad \beta_{mm} - \sum_{r=1}^{R} \mu_{mr} = 0, \\ \sum_{g=1}^{3} \theta_{rg} - \mu_{mr} = 0, \qquad \sum_{m=1}^{M} \delta_{km} - \sum_{r=1}^{R} \varphi_{kr} = 0, \end{gathered} \tag{vii}$$

$$\theta_{rg} = \theta_{gr}, \qquad \alpha_{kl} = \alpha_{lk} \tag{viii}$$

where this minimization problem aims to estimate the parameters that minimizes the distance in output space of the decision making units (states) from the output isoquant representing technical efficient production, subject to a set of constraints. We assume that the output plans are feasible, and that the output set satisfies (i) monotonicity with respect to desirable and undesirable outputs and in inputs (ii-iv), concavity in desirable and undesirable outputs (v), and null-jointness in desirable and undesirable outputs (vi). We also impose the translation property and symmetry (vii-viii). As in the stochastic estimation described by Equation (13), all variables were normalized by their overall mean.

This method was used mainly to see about robustness of the stochastic estimation. For both estimating approaches we obtained the directional distance to the frontier, the rate and biases of technical change, and the shadow prices of the undesirables. Technological change is obtained using Equation (4) and equation (13) for the stochastic frontier approach[10]

$$\frac{\partial \vec{D}_o}{\partial t} = v_1 + v_{11} t_i + \sum_{k=2}^{4} v_{1k} \mathrm{x}_{\mathrm{k-1,i}} + \sum_{r=1}^{3} \lambda_{1r} \mathrm{b}'_{\mathrm{r}} \tag{19}$$

[10] Its estimation for the non-stochastic approach takes into account all coefficients (including those with respect to the desirable output) and since the translation property is imposed directly by the constrain (vii). The directional output distance functions represented in Equation (18) considers a quadratic functional form described in Equation (12).

This is the Hicks neutral rate of expansion (or contraction) of the production possibility frontier (PPF). Hicksian biases in equation (9) indicate if the slope of the frontier changed as a result of technical change while Overall biases in equation (10) indicate if the share of that output has changed. Hicksian biases are

$$B_{GDP,CO2e}(GDP, CO_2e, x, t) \equiv \left[\frac{\lambda_{1,CO2e}}{\nabla\vec{D}_{CO_2e}} - \frac{\lambda_{1,CO2e}}{\nabla\vec{D}_{GDP}}\right]t \tag{20}$$

where by translation property $\lambda_{1,CO2e} = \eta_{1,GDP}$, and $\nabla\vec{D}_{CO_2e}$ and $\nabla\vec{D}_{GDP}$ represent the first derivative of the directional distance function with respect to the undesirable and desirable outputs, respectively. In addition,

$$\begin{aligned} \nabla\vec{D}_{CO_2e} &= \theta_r + \theta_{11}b_{11} + \sum_{r=1}^{3} \varphi_{k1}x_{ki} + \mu_{11}y_1 + \lambda_{1,CO2e}t_i \geq 0 \\ \nabla\vec{D}_{GDP} &= \beta_1 + \beta_{11}y_1 + \sum_{k=1}^{3} \delta_{k1}x_{ki} + \mu_1 b_{11} + \eta_{1,GDP}t_i \leq 0 \end{aligned} \tag{21}$$

by the monotonicity property, i.e. the distance function should increase with undesirable outputs and decrease with desirable outputs. These properties will be cheeked after estimation. As an example, equation (20) illustrates the pairwise bias of GDP and CO_2e. The overall bias can be calculated as a weighted sum of the pairwise biases.

The shadow price is obtained using Equation (8)

$$q_{CO_2e} = -p_{GDP}\left[\frac{\theta_r + \theta_{11}b_{11} + \sum_{r=1}^{3} \varphi_{k1}x_{ki} + \mu_{11}y_1 + \lambda_{1,CO2e}t_i}{\beta_1 + \beta_{11}y_1 + \sum_{k=1}^{3} \delta_{k1}x_{ki} + \mu_1 b_{11} + \eta_{1,GDP}t_i}\right], \tag{22}$$

and should be positive. Equation (13) and (16), the stochastic model, is estimated using Stata 14 while the minimization problem described in Equation (18) is solved using GAMS.

5. Results and policy implications

Two approaches were used to estimate a model with one desirable output, GDP, and one undesirable output, CO_2e. In addition a stochastic approach was used to estimate the output directional distance function with three undesirable outputs, CH_4, N_2O and CO_2. The symmetry and the translation properties were imposed in all models while monotonicity was checked in the stochastic approach and imposed in the non-stochastic approach.[11] Table 2 presents the estimation results for all three models.

[Table 2]

The distance (technical inefficiency) estimated using Equation (14) and (15) is displayed in Figure 8[12] by state. The average is 0.37, which means that a simultaneously expansion of normalized GDP of 37% and a 37% contraction of normalized CO_2e is possible by decreasing technical inefficiencies. As expected, technical inefficiency decreases when more outputs are added to the model. By eliminating technical inefficiency, it is possible, on average, to expand normalized GDP by 18% and simultaneously contracts normalized emissions of CO_2, CH_4 and N_2O by 18%. Technical efficiency seems to have improved in the region, which results in decreases in greenhouses gases emission.

[Figure 08]

Technical change, the objective of this study, can also be seen as responsible for reductions in greenhouse gases. For the whole region, technical change over the period (1990-2009) was 0.065[13]. It indicates that normalized GDP is expanded by 6.5% while normalized CO_2e is simultaneously

[11] For the model with two outputs, 9 GDP predictions and 19 CO2e predictions out of 180 violated the monotonicity. For the model with four outputs, monotonicity was violated in 1, 16, 135, and 8 observations out of 180 for GDP, CO_2, CH_4 and N_2O, respectively.

[12] It is also in Table 4, but more aggregated.

[13] It is not statistically significant. In Table 3, we display technical change per state, which for a few states it is statistically significant.

contracted by 6.5% due to innovations. Figure 9[14] displays the pattern of evolution of technical change per state.

[Figure 09]

Figure 9 shows an increase in technical change over the period for some states such as Mato Grosso (MT), Para (PA), Tocantins (TO), and Maranhão (MA) as expected, since they form the "arc of deforestation" or the agricultural frontier. A few states show a decreases of technical change over time – Acre (AC), Amapá (AP), and Roraima (RR). It is interesting to notice a break in the evolution of technical change around 2004, when deforestation control policies were introduced. A per state and selected periods analysis is performed on Table 3, where it is shown that our estimate of technical change is significantly different from zero in some states and sub-periods.

None of the states show a statistically significant rate of technical progress in the 1990-1995 years. Some states have significant rates of technical change in the during 1996-2004 and during 2005-09. Considering only the observations that satisfy output monotonicity[15], in the third period, states on the agriculture frontier have experienced a statistically significant technical progress[16] of 0.149[17]. It is consistent with Figures 2 and 3, where MT shows increasing GDP and a decreasing CO_2 emissions.

[Table 3]

The rate of technical change estimated indicates an upward shift of the production frontier but it does not give information about the rotation of the production possibility frontier around the directional expansion assumed. This is the change in the MRT between outputs as a result of technical change. This information is obtained from the Hicksian pairwise biases estimated, using

[14] These graphs should be read with caution since each graph has a different vertical axis.
[15] Preliminary results for technical change considering all observations are shown in Table 3.
[16] Gomes and Braga (2008) found a growth rate for TFP for this region of 7.34% in 2004. Although is a different concept, it shed light on these results. Bragagnolo et al. (2010) found a technical change rate on average of 8% for the states on agricultural frontier considering the period of 1995-2005 [i.e. PA (8.7%), TO (8.9%), MA (4.9%), MT (7.6%)]. Helfand et al. (2015) found a rate of technical change for the north of Brazil of 7.09% using the period 1985-2006.
[17] This value is affected by outliers related to the state of Para. The average of technical progress for the same period for the states of MA, RO and TO were 0.095, 0.053 and 0.092, respectively.

Equation (20) and displayed in Table 4. We found a positive sign ($B_{GDP,CO2e} > 0$) of the pairwise bias between GDP and CO_2e which suggests that technical progress is biased towards production of CO_2e emission and against GDP. The shadow price of CO_2e in terms of GDP, is also displayed in Table 4. Figure 11 illustrates the increasing MRT due to technical progress. There is no need to estimate an overall bias for the model with two outputs since it is calculated by the weighted sum of pairwise biases.

[Table 4]

Table 4 shows the pairwise bias between GDP and CO_2, CH_4, and N_2O. Over the period, CO_2 emission become less *costly* ($B_{GDP,CO2e} < 0$), as is also reflected in in the shadow price of CO_2 estimated. The overall bias suggests a similar behavior. This suggests that technological progress has been biased toward production of GDP and against GHG emissions.

Results from the programming calculation of the directional distance function are displayed in Table 5. We found a higher technical average inefficiency of 0.54, a lower technical progress of 0.017, and a similar result for the pairwise bias (positive) between GDP and CO_2e. Technical progress, as in the stochastic estimation, is higher in the states in the agricultural frontier.

[Table 5]

We obtain an output set for states that are technical efficient in different years using the parameters obtained from the minimization problem[18] (Equation 16). We followed Färe et al. (2005) and use the quadratic formula to obtain the estimated GDP for each unit of CO_2e, given fixed input quantities. For example, Mato Grosso was technical efficient ($\vec{D}_o = 0$) in 2009, where 224432 of capital and 83892 of labor was used. Since technical efficient units are on the boundary of the output set, we estimated the GDP that would keep them at the boundary for different values of CO_2e, given fixed input quantities. Färe et al. (2005) considered undesirable output starting at zero units and increasing by 0.25, while we considered starting at zero and increasing by 0.1. We performed the same exercise for four years (2009, 2002, 1997, and 1991) and different technical

[18] We opted for using the parameter obtained in this method since theoretical properties were imposed.

efficient units (MT, TO, AP, and PA). Values for inputs in each case are at the bottom of the Figure 11[19].

[Figure 10]

The output set has an inverted U shape given the concavity property. Technical progress expanded the output set across the years and moved it closer to the vertical axis, which means it allowed producing more GDP per CO_2e (increasing the slope of the boundary).

Shadow prices are estimated based on the dual relationship between normalized revenue and the output distance function. It is in Figure 11 as a tangent line to the boundary of the output set. Results for stochastic and non-stochastic models are displayed in Table 4 and 5. On average, the shadow price of CO_2e in terms of GDP (US$ 45.55[20]) is higher than the CO_2 in terms of GDP (US$ 15.78), as expected. For 2006, these values are US$ 25.48 and US$10.71, respectively.

5.1.Policy Implications

Several regulations to decrease deforestation and indirectly GHG emissions have been introduced in the last 10 years. Galford et al. (2013) also discuss recommendations on tillage practices that would decrease release of CO_2 from the soil. Soares-Filho et al. (2014) point out modification of the Forest Code in 2012 that lead to the creation of a market mechanisms such as the *Environment Reserve Cota* (CRA). Boner et al. (2010) investigate the viability of applying payments for environmental services (PES) through REDD+ and they find that this system would not substitute command-control policies that took place several years ago. They argue that PES need policies that would support the development of a market mechanism.

Nonetheless, none of these policies aims to directly correct technical inefficiencies and generate technical progress. We have shown that innovations and catching–up to the most efficient units could reduce emissions and simultaneously increase output in, especially states on the agriculture

[19] As in Färe et al. (2005), the output set was built aiming to show its expansion due to technical change. GDP and CO_2e quantities are calculated considering the estimated technology (parameters), thus it aims to show the behavior of the technology instead of predicting quantities.
[20] A 2006 exchange rate was used to estimate the shadow price – US$ 1 is equivalent to R$ 2.57.

frontier. These reductions can be achieved by enhancing infrastructure, credit availability, and technical assistance to farmers that adopt ‘clean’ agricultural practice[21]. It is important to notice that Brazil just committed[22] in COP 21 (Paris) to reduce greenhouse emissions by 37% (below 2005 levels) by 2025.

6. Conclusions

This paper evaluates the impact of technical change on agricultural production and greenhouse gas emissions in the Amazon Forest region in Brazil during the period 1990-2009. Three quadratic directional distance function were estimated by two different approaches – stochastic and non-stochastic. We present in this paper preliminary results.

These results indicate technical progress in the region, more important in the states in the ‘arc of deforestation’. Maranhão, Roraima and Tocantins have shown a simultaneous expansion of normalized GDP of around 8% and contraction of normalized CO_2e emission of 8% during the period of 2005/2009. The pairwise bias between GDP and CO_2e emission suggests an increase in emission reduction cost of CO_2e in terms of GDP due to technical progress.

Brazilian government policies have achieved positive results in terms of decreasing deforestation and greenhouse emissions. However, policies toward enhancing technical efficiency and building a foundation to technical change might have superior results.

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[21] By clean, we are referring to production technologies that allow increasing agriculture production simultaneously to decreasing greenhouse emission (and deforestation).

[22] This information is on the Intended Nationally Determined Contribution on COP21 website (http://www4.unfccc.int/submissions/INDC/Published%20Documents/Brazil/1/BRAZIL%20iNDC%20english%20FINAL.pdf).

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FIGURES AND TABLES

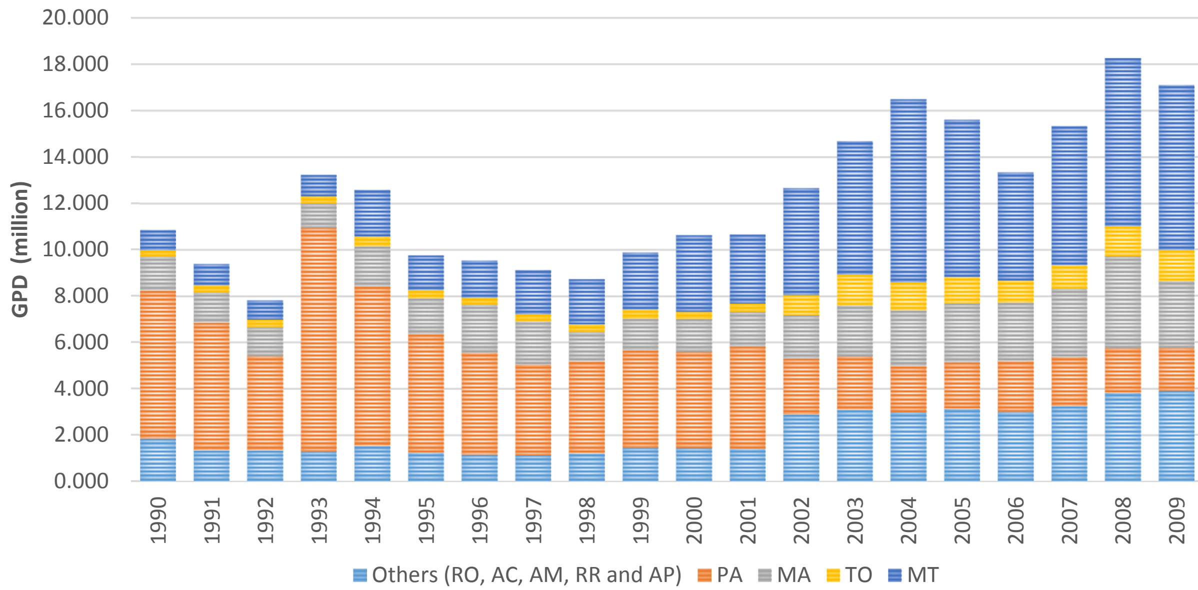

Figure 02 – Agricultural *Gross Domestic Product* (additional value) for selected states and per year
Source: Institute for Applied Economic Research (IPEA, 2015).

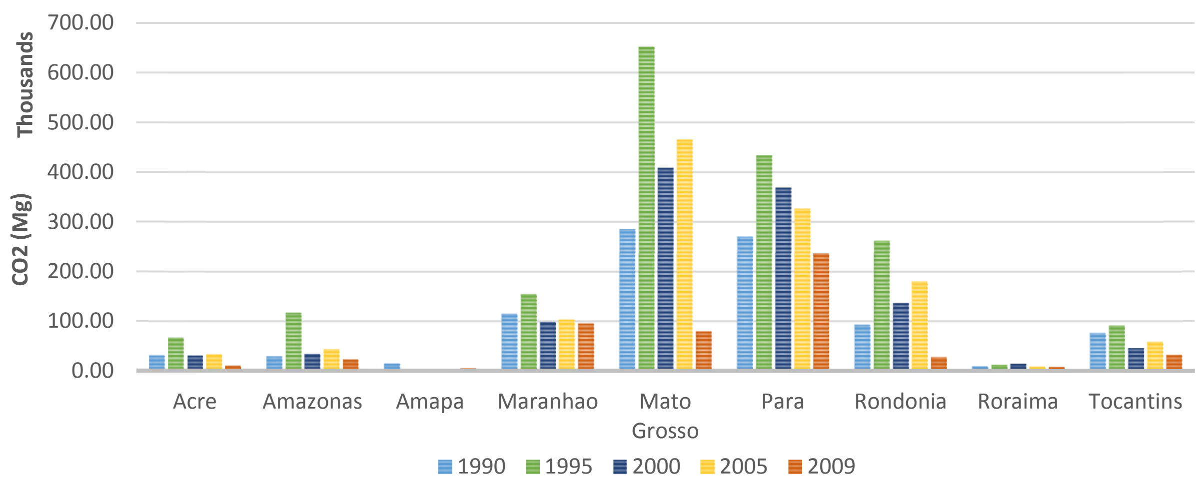

Figure 03 – CO_2 emission that considers liming for agriculture per states and year
Source: SEEG (2015).

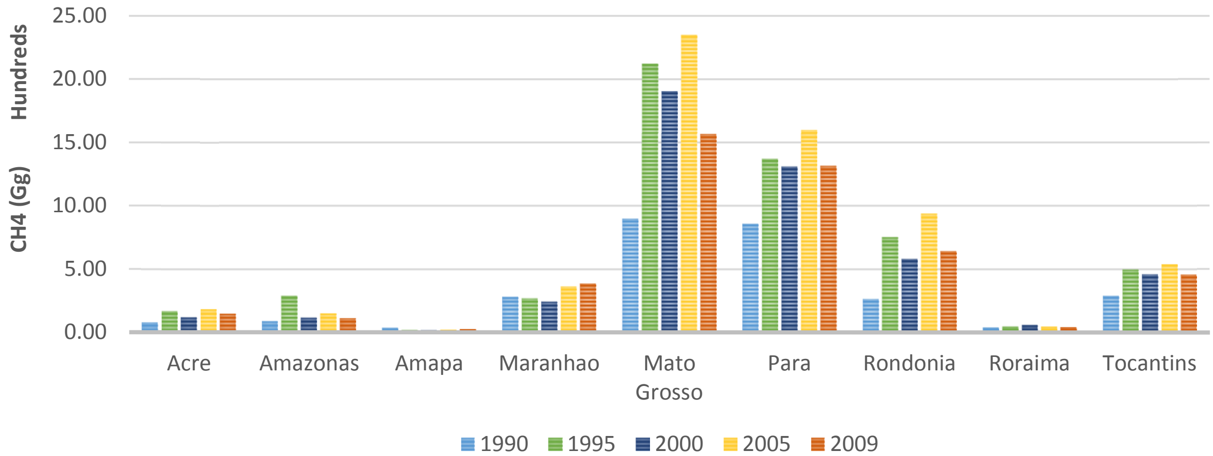

Figure 04 – CH_4 emission that considers liming for agriculture per states and year
Source: SEEG (2015).

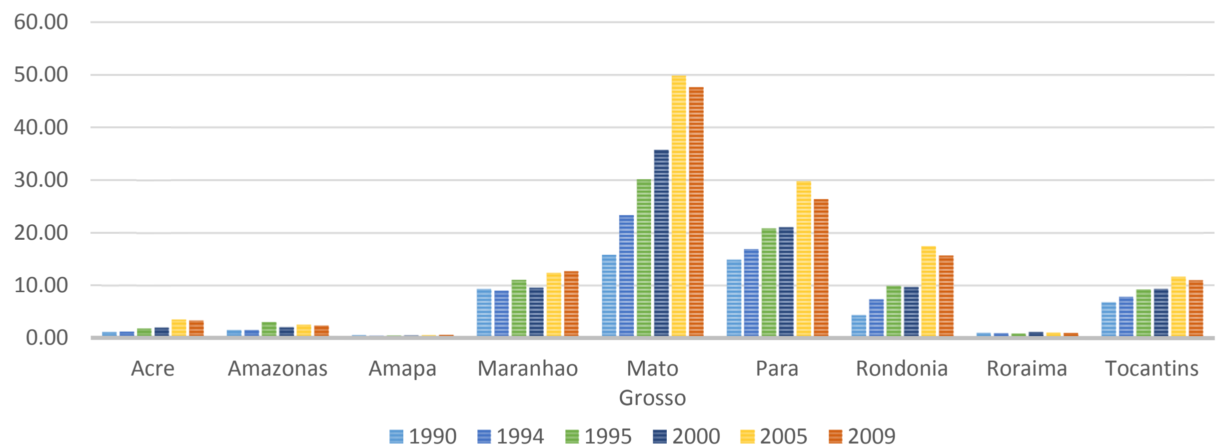

Figure 05 – N_2O emission that considers liming for agriculture per states and year
Source: SEEG (2015).

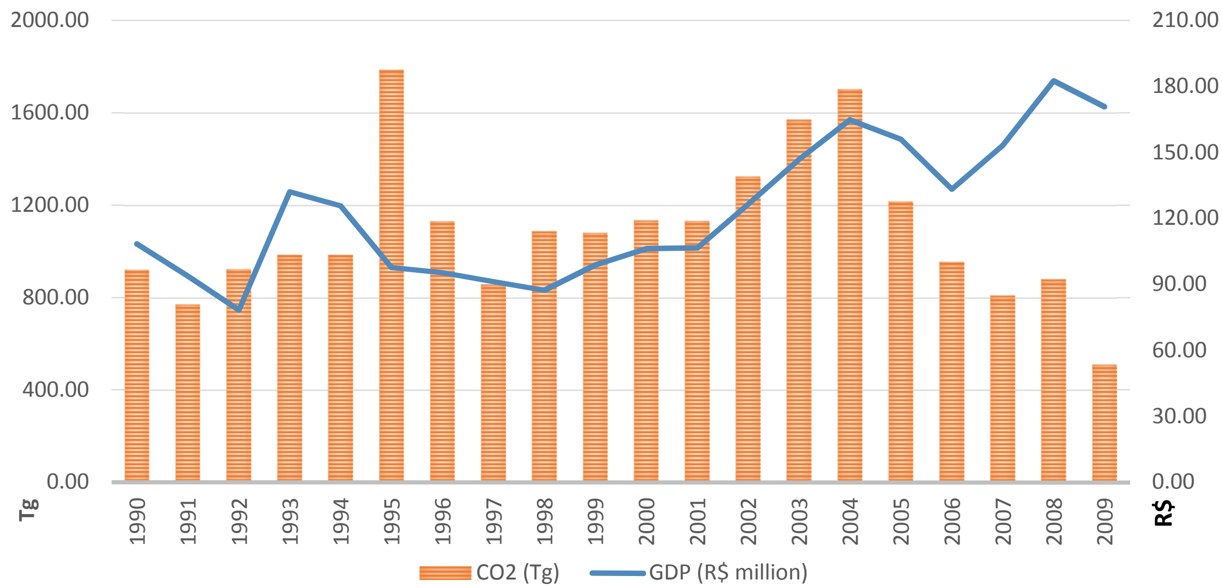

Figure 06 – Agricultural *GDP* and CO_2 emission for Amazon Forest Region per year
Source: SEEG (2015) and IPEA (2015).

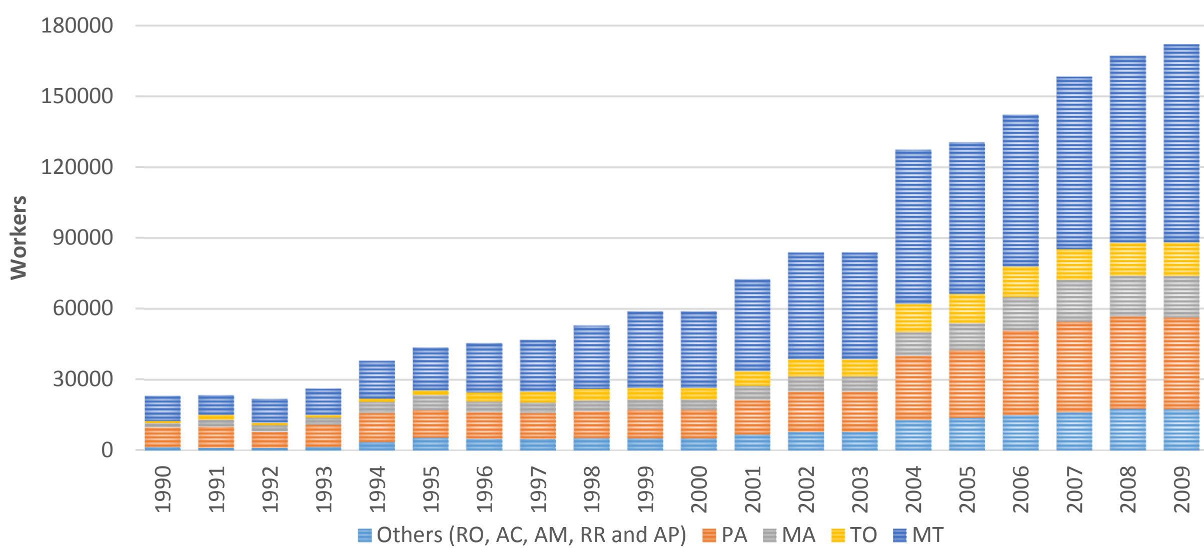

Figure 07 – Hired workers per year and group of states
Source: CAGED (2015).

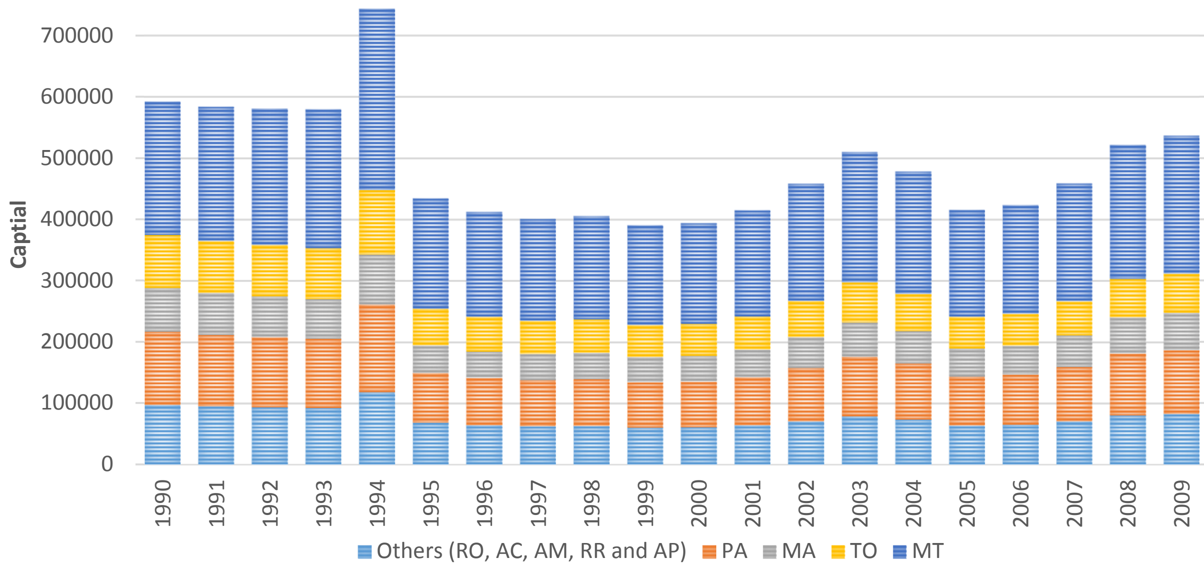

Figure 08 – Agricultural real stock of Capital per state and year
Source: Author using data from (IPEA, 2015).

Table 1 – Descriptive statistics for the states in the Legal Amazon, Brazil, 1990-2009

		AC	AM	AP	MA	MT	PA	RO	RR	TO	LA
GDP *(R$1000)*	*Mean*	240361.3	679453.4	98659.07	1968645	3553266	3970425	1027727	82763.06	657269.6	**1364286**
	Min	59707.64	274252.7	60588.49	1028790	825142.4	1865078	543351.1	16018.88	265884.7	**16018.88**
	Max	595177.9	1141058	152749.8	3975933	7878815	9657855	2055593	202201.3	1332287	**9657855**
CO_2e *(Mg GWP)*	*Mean*	32448.94	48522.68	3589.69	111417.7	448270.4	343124.6	148953.5	15771.16	66742.87	**135426.8**
	Min	13371.31	22491.51	335.97	72354.35	126231.7	229539.5	44986.48	5645.78	43955.18	**335.9711**
	Max	70782.13	123827	23862.98	169588.7	802101.4	540277.9	280318.9	34037.32	104300.2	**802101.4**
CO_2 *(Mg)*	*Mean*	29078.34	44938.75	3048.80	98381.85	399761.1	310930.9	132690.9	14351.21	54796.49	**120886.5**
	Min	9232.1	20454.34	0	61512.86	78622.16	208966	26662.64	4643.68	30955.9	**0**
	Max	66780.67	116866.2	22665.63	153914.6	725668.4	490351.4	261514.8	31731.88	91075.52	**725668.4**
CH_4 *(Mg)*	*Mean*	127.27	139.01	18.91	291.27	1788.66	1218.36	611.50	52.82	431.28	**519.90**
	Min	59.56	76.08	10.92	230.76	821.10	761.61	261.43	35.04	285.24	**10.92**
	Max	219.06	286.89	48.96	385.63	2861.41	1915.61	981.47	90.50	537.03	**2861.41**
N_2O *(Mg)*	*Mean*	2.25	2.14	0.46	10.42	35.31	21.31	11.03	1.00	9.32	**10.36**
	Min	0.99	1.42	0.28	8.59	15.84	14.77	4.32	0.84	6.70	**0.28**
	Max	3.54	3.02	0.62	13.21	52.72	31.28	17.43	1.30	11.63	**52.72**
Capital *(Units)*	*Mean*	14481.05	15231.55	3391.60	53903.46	197270.9	93692.49	34140.38	9464.64	64858.46	**54048.28**
	Min	10739.03	11199.43	2427.03	41600.93	161782.7	73614.52	28459.13	6175.09	51922.75	**2427.03**
	Max	21733.69	22976.15	4821.86	81445.72	295679.9	142877.2	51678.29	17500.38	105233.3	**295679.9**
Labor *(Sum of employee)*	*Mean*	1611.9	1462.7	461.3	7570.7	38309.6	18549.4	3883.15	402.8	6480.95	**8748.06**
	Min	179	313	39	1873	8185	6882	412	24	927	**24**
	Max	2928	2938	1290	17624	83892	39013	9948	1225	14235	**83892**

Source: Own elaboration

Table 2 – COLS parameter estimates for $\vec{D}_o$ in 9 states of the Legal Amazon, Brazil, 1990-2009

	COLS *(GDP & CO_2e)*	**Nonlinear Programming** *(GDP & CO_2e)*	**COLS** *(4 outputs)*
GDP	-0.389***	0.0001	-0.066
GDP square	-0.091***	-0.0141	0.072
CO_2e square	-0.091***	-0.0141	-
GDPCO_2e*	-0.091***	-0.0141	-
*GDP*Capital*	-0.056	0.0052	-0.016
*CO_2e*Capital*	-0.056	0.0052	-
*GDP*Labor*	-0.08	0.0014	0.037
*CO_2e*Labor*	-0.08	0.0014	-
CO_2e	0.611***	1.0001	-
CO_2	-	-	0.753***
CO_2 square	-	-	-0.5937**
CH_4	-	-	-0.976
CH_4 square	-	-	-2.459**
N_2O	-	-	1.156**
N_2O Square	-	-	-1.091
Labor	-1.37***	-0.2426	-0.698***
Labor square	-0.076	-0.005	0.022**
Capital	-0.119	-0.1349	-0.347**
Capital square	0.037	-0.0319	0.227***
*Capital*Labor*	-0.11*	0.0111	-0.057*
*CO_2*Capital*	-	-	-0.353***
*CO_2*Labor*	-	-	0.039
*CH_4*Capital*	-	-	0.696**
*CH_4*Labor*	-	-	-0.067
*N_2O*Capital*	-	-	-0.359*
*N_2O*Labor*	-	-	0.064
*CO_2*N_2O*	-	-	-0.366
*CO_2*CH_4*	-	-	1.031**
*N_2O*CH_4*	-	-	1.399
GDPN_2O*	-	-	0.072
GDPCH_4*	-	-	-0.0581
GDPCO_2*	-	-	-0.028
Trend	0.005	-0.0006	0.0061
Trend square	-0.001	-0.00003	-0.0007
*Trend*Capital*	-0.021	0.0064	-0.031***
*Trend*Labor*	0.09***	0.0118	0.029***
*Trend*GDP*	0.025***	0.00003	-0.0054
TrendCO_2e*	0.025***	0.00003	-
TrendCO_2*	-	-	-0.024*
TrendCH_4*	-	-	-0.011
TrendN_2O*	-	-	-0.03
Constant	1.35**	-0.822	-0.618
State Fix Effects	*Yes*	*Yes*	*Yes*

Note: *** for p-value bigger than 0.01, ** bigger than 0.05, and * bigger than 0.1.
Source: own elaboration.

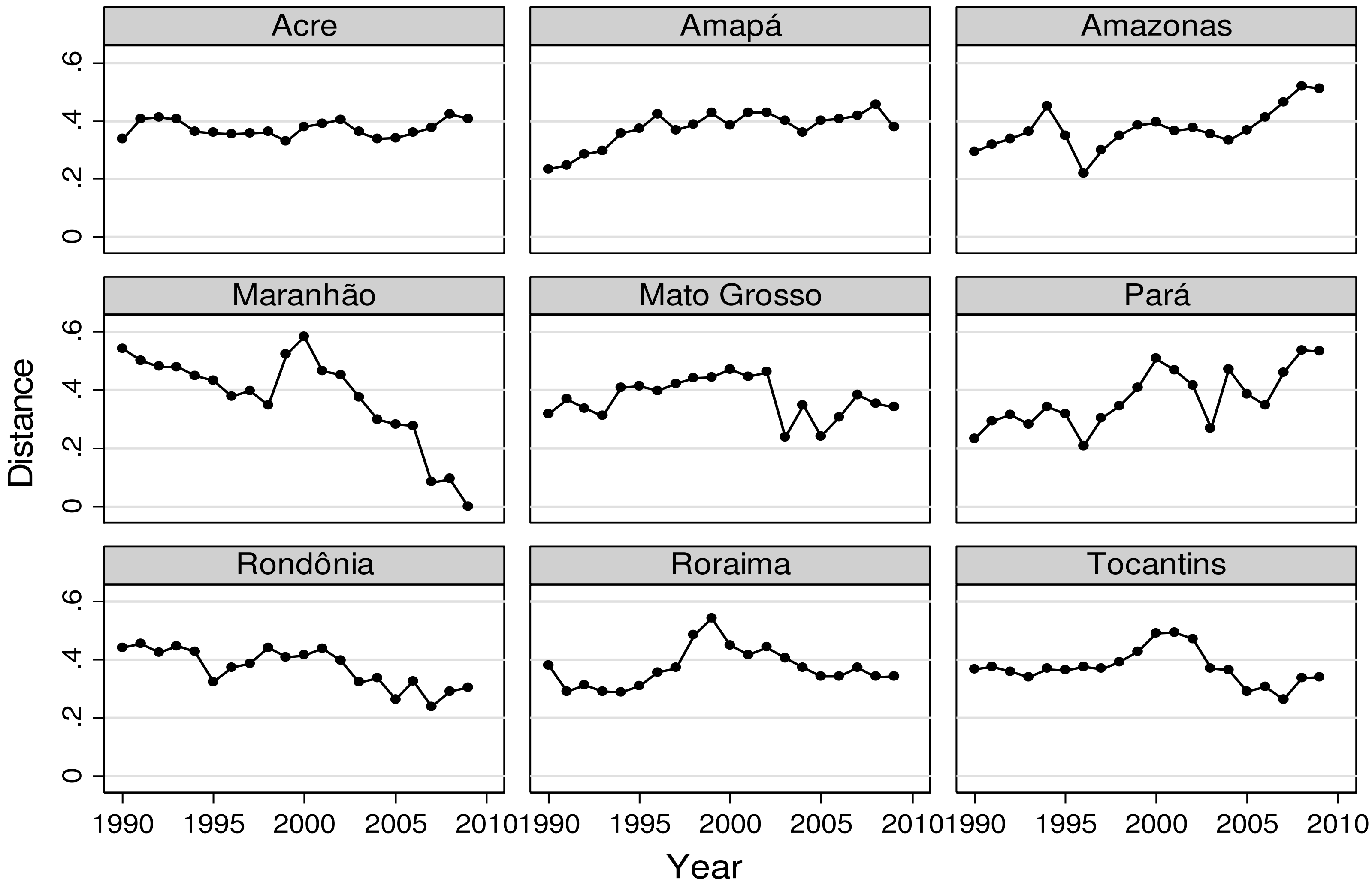

Figure 09 – Distance (Technical inefficiencies)
Source: Own elaboration.

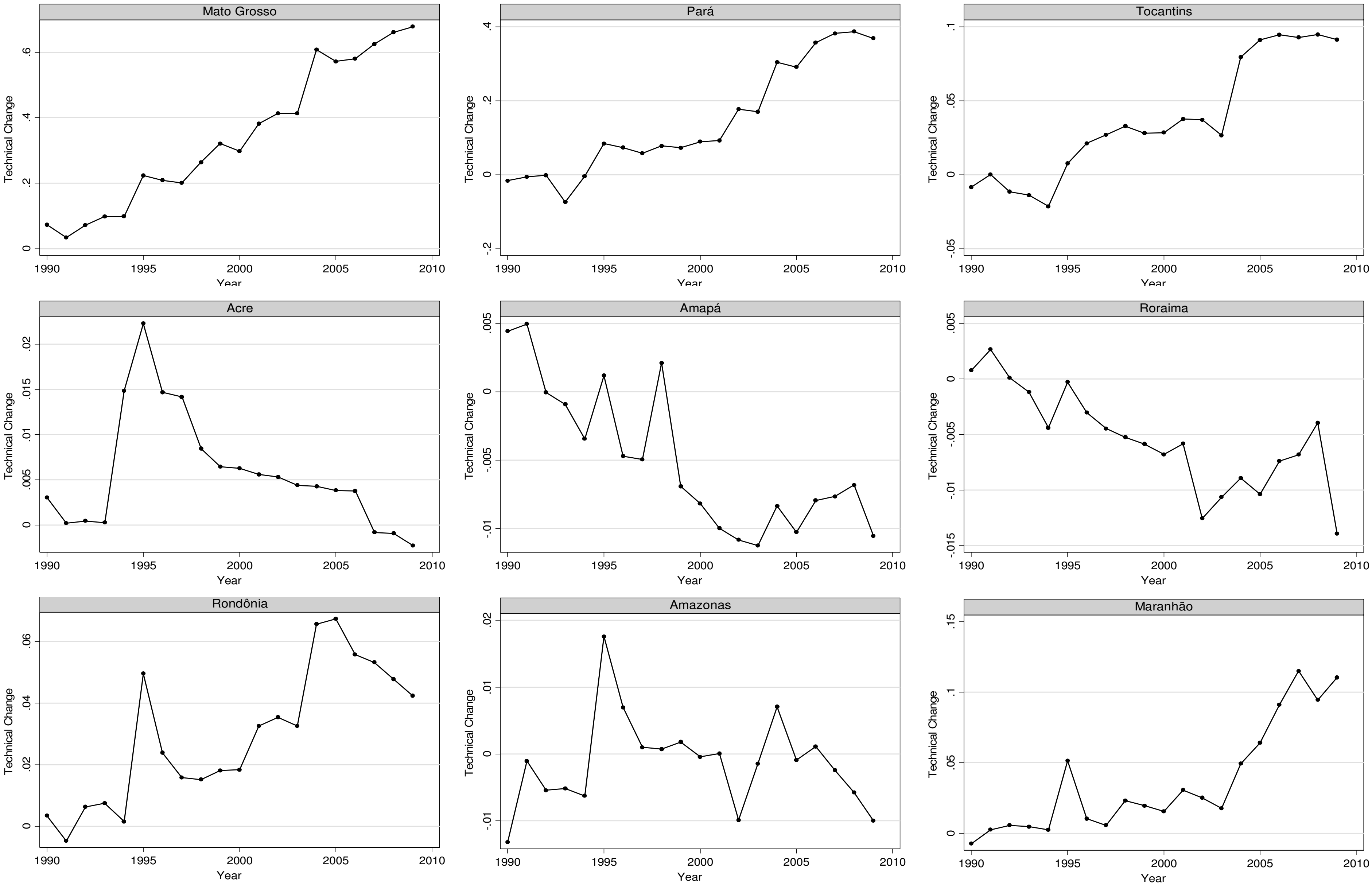

Figure 10 – Technical Change (Equation 5)
Note: Vertical axis changes given different pattern of technical change across states.
Source: Own elaboration.

Table 3 – Technical change per state and selected periods using COLS for the model with GDP and CO_2e

		States									
Periods		**AC**	**AP**	**AM**	**MA**	**MT**	**PA**	**RO**	**RR**	**TO**	**Total**
1990/95	TC	0.007	0.001	-0.002	0.010	0.100	-0.003	0.011	0.000	-0.008	0.013
	p-value	*0.666*	*0.864*	*0.567*	*0.655*	*0.159*	*0.592*	*0.611*	*0.897*	*0.601*	*0.624*
1996/04	TC	0.008	-0.007	0.001	0.022	0.345	0.124	0.029	-0.007	0.035	0.061
	p-value	*0.315*	*0.319*	*0.703*	*0.159*	*0.000*	*0.000*	*0.016*	*0.326*	*0.024*	*0.207*
2005/09	TC	0.001	-0.009	-0.004	0.095	0.623	0.357	0.053	-0.008	0.093	0.133
	p-value	*0.861*	*0.539*	*0.811*	*0.000*	*0.000*	*0.000*	*0.011*	*0.565*	*0.000*	*0.310*
Total	TC	0.006	-0.005	-0.001	0.037	0.341	0.144	0.029	-0.005	0.037	0.065
	p-value	*0.557*	*0.537*	*0.689*	*0.268*	*0.048*	*0.178*	*0.193*	*0.557*	*0.191*	*0.358*

Source: Own elaboration.

Table 4 – Main results obtained using COLS on the $\vec{D}_o$

Period	Distance (GDP & CO_2e)	Distance (4 outputs)	Bias $B^t_{GDP,Co2e}$	Bias $B^t_{GDP,Co2}$	Bias $B^t_{GDP,CH4}$	Bias $B^t_{GDP,N2O}$	Overall Bias For GDP	Shadow Price of CO_2e (US$)	Shadow Price of CO_2 (US$)
1990/95	0.3828 (0.068)	0.1816 (0.073)	0.531 (0.191)	-0.609 (0.244)	-0.242 (0.226)	0.143 (0.259)	0.036 (0.172)	5.34	25.37
1996/04	0.395 (0.066)	0.1981 (0.039)	3.667 (1.316)	-2.511 (1.223)	-1.312 (1.898)	-0.121 (0.265)	-3.88 (0.58)	16.32	13.34
2005/09	0.346 (0.108)	0.1805 (0.074)	20.273 (7.276)	-2.418 (1.112)	-3.551 (7.594)	-0.116 (0.342)	-2.09 (1.69)	176.32	9.55
Overall	0.373 (0.081)	0.1887 (0.061)	6.084 (2.184)	-1.953 (0.913)	-1.157 (2.01)	-0.045 (0.282)	-2.261 (0.739)	45.55	15.78

Note: Standard errors in the parentheses.
Source: Own elaboration.

Table 5 – Main results obtained using Nonlinear Programming on the $\vec{D}_o$

State/Period	Distance	Technical Change (TC)	TC (x 100)	Bias $B^{t}_{GDP,Co2e}$	Shadow Price (US$)
RO	0.79957	0.00844	0.84	0.01409	181.26
AC	0.13655	0.00300	0.30	0.09170	1438.01
AM	0.23616	0.00290	0.29	0.03371	430.26
RR	0.08011	0.00077	0.08	0.82062	16601.84
PA	1.15033	0.03539	3.54	0.00626	58.51
AP	0.02546	0.00013	0.01	1.13265	11985.88
TO	0.08154	0.01556	1.56	0.05336	801.59
MA	0.34839	0.01577	1.58	0.01229	157.59
MT	2.03137	0.07433	7.43	0.00561	79.94
1990/95	0.41589	0.12963	12.96	0.22859	6152.79
1996/04	0.67768	0.03704	3.70	0.20076	2321.42
2005/09	0.45422	0.06667	6.67	0.29504	2095.52
LA Region	0.54338	0.01747	1.74	0.23288	3405.12

Source: Own elaboration.

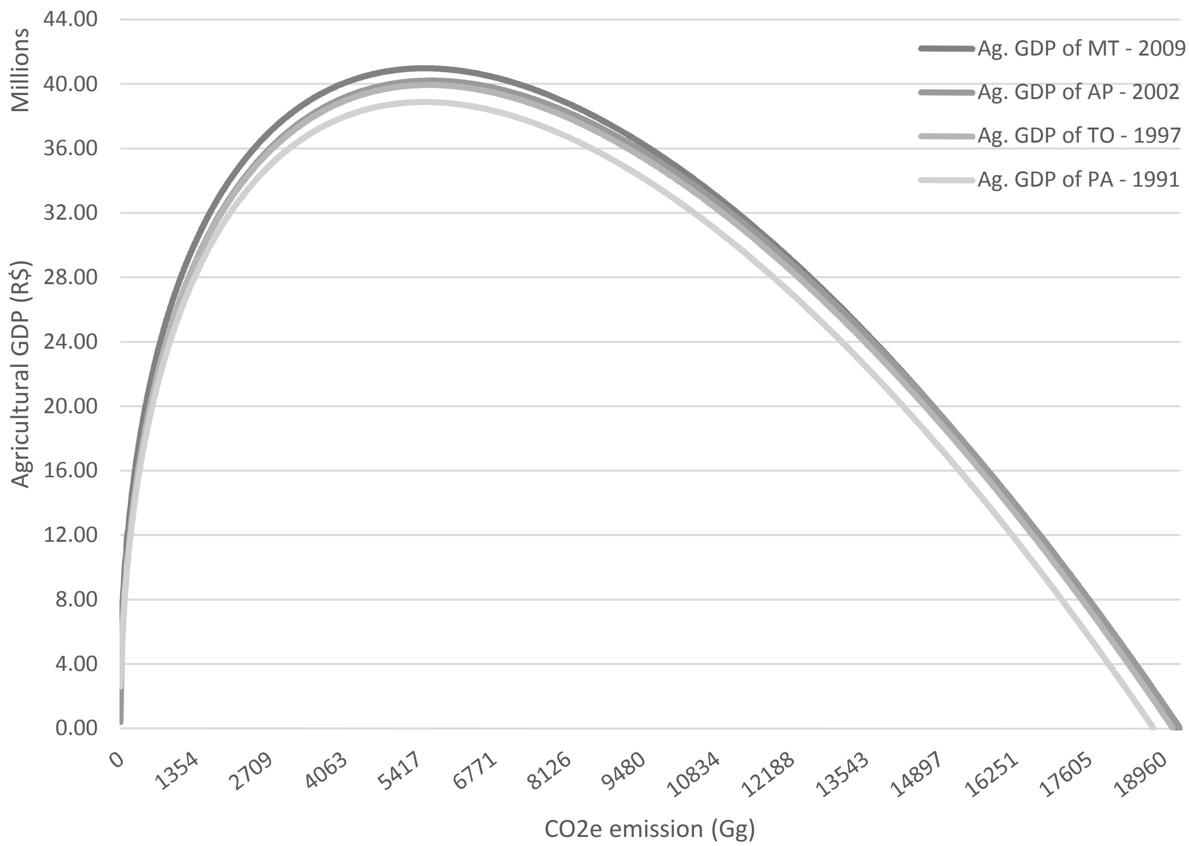

Figure 11 – Output set [*P(x)*] for selected efficient states in 1991, 1997, 2002 and 2009
Note: Capital and labor used to build the output set was 224432 and 83892 for 2009, 3088 and 261 for 2002m 54547 and 4422 for 1997, and 116594 and 8999 for 1991.
Source: Own elaboration.

APPENDIX A

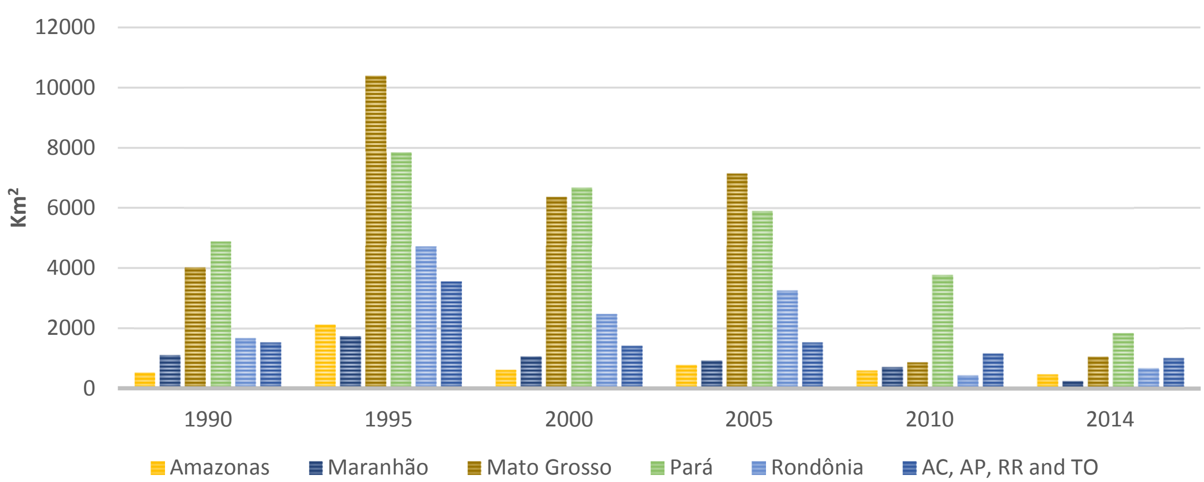

Figure A1: Amazon deforestation (in km^2) per state during the period 1990-2014.
Source: PRODES-INPE (2014)**.**

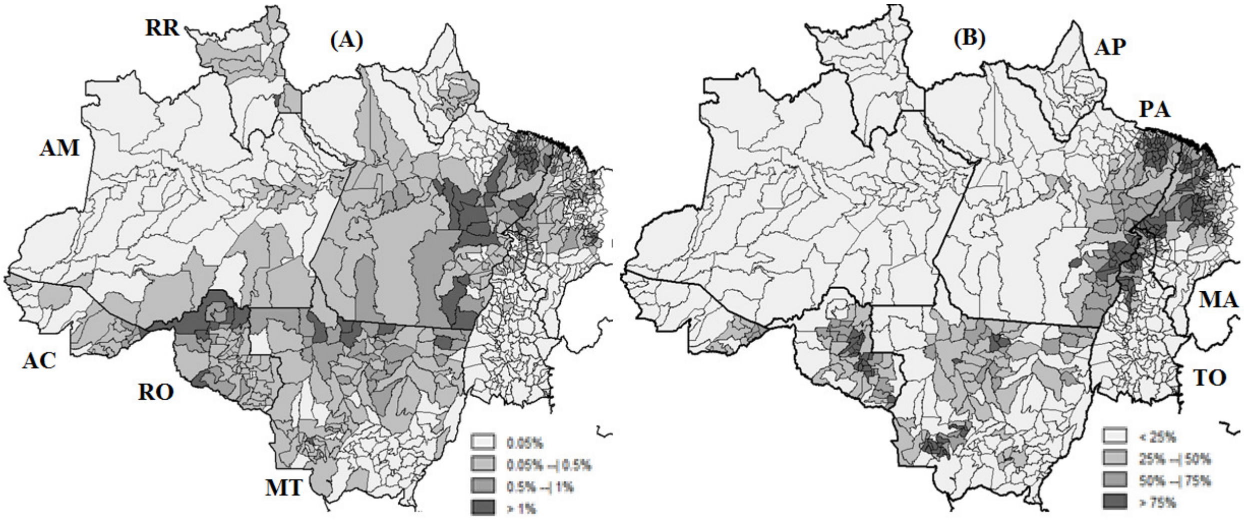

Figure A2: Deforestation in 2006 and until 2006 (in km^2).
Source: PRODES-INPE (2014)**.**

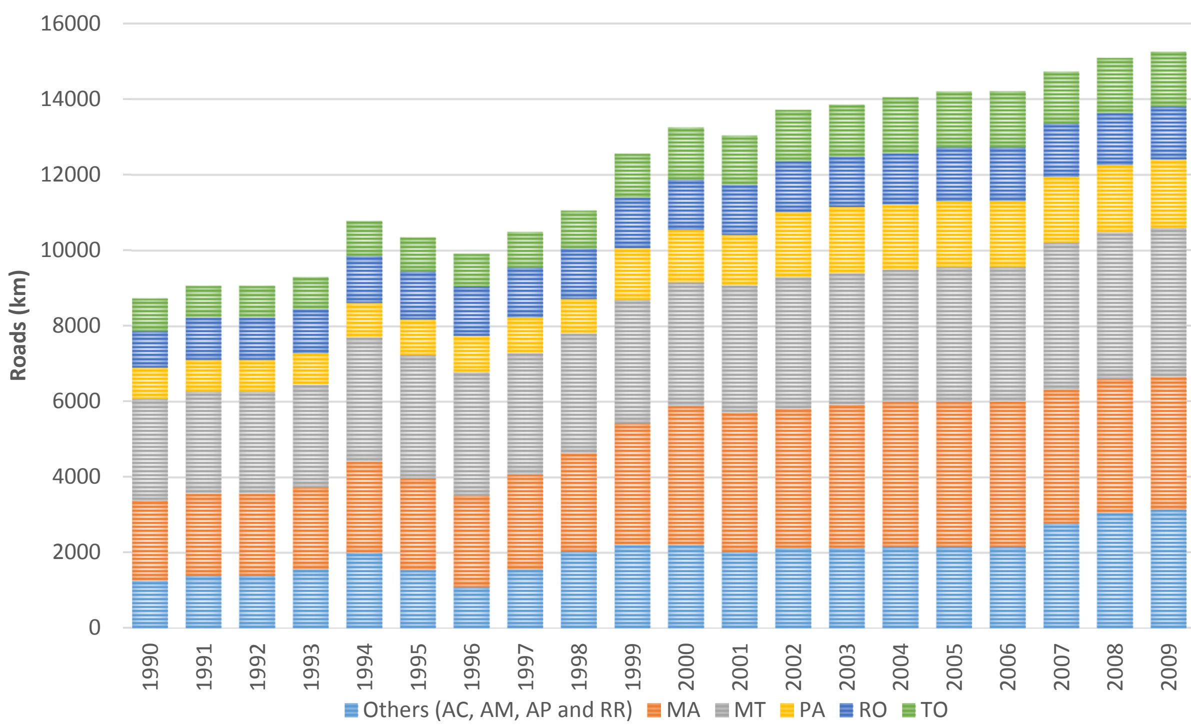

Figure A3 – Roads (km) per selected state and year
Source:

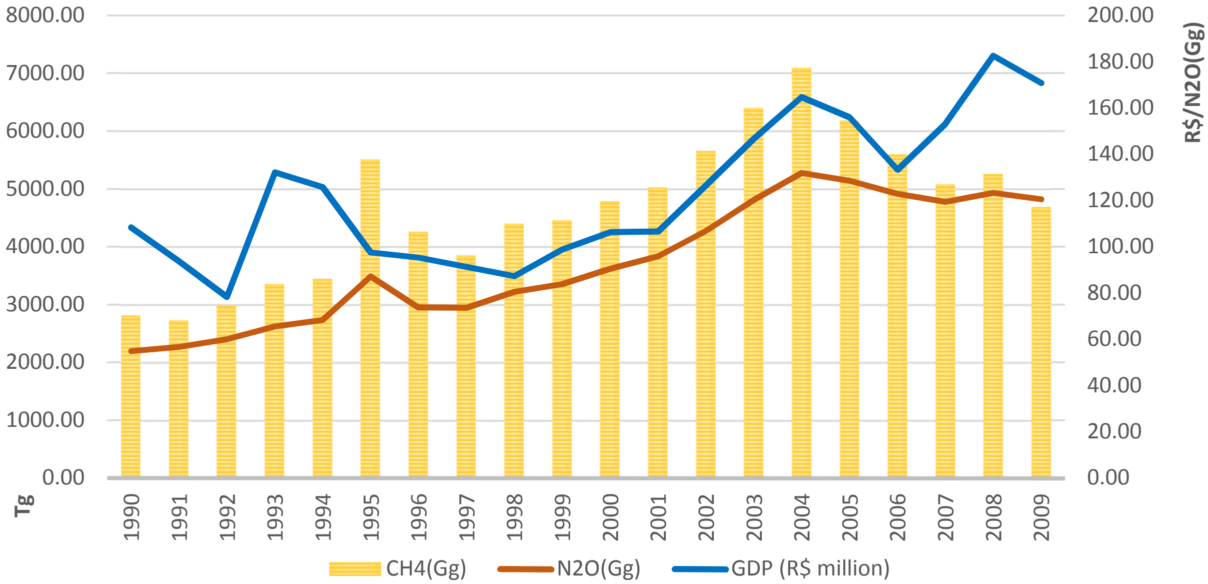

Figure A4 – Agricultural *GDP*, CH_4 and N_2O emission for Amazon Forest Region per year
Source: SEEG (2015) and IPEA (2015).