

# ***Blue-Green Municipalities: Economic analysis of selected counties in São Paulo State***

*Inter-American Institute for Global Change Research – IDRC Grant: Land use, biofuels and rural development in the La Plata Basin*

Activity 1- Potential land cover and land use change in La Plata Basin induced by biofuels expansion - PI: Maria Victoria Ramos Ballester

*Grant extension: “Economic analysis of selected counties in São Paulo State”*

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## **1. INTRODUCTION**

Sao Paulo state is the biggest producer of sugarcane in Brazil. Recently, the area for sugarcane has been increased in the majority of its counties, especially in the western region of the state. Satellite images and data of production and area cultivated indicate that the land use has changing quickly in this region: in general, pastures have been replaced by sugarcane. Indirectly, this land use change can also impact forest areas in the Sao Paulo state. It is expected that the expansion of sugarcane areas pressure forest areas. As a result, it is expected that the higher the increase in sugarcane area in the last years, the higher the decrease in forest area in each county. Besides this important context, obviously land use can also be determined by some socioeconomic characteristics of each county and by public policies involving land tenure and forest protection. However, investigations on land use/land cover (LUCC) change and forest management are limited by a lack of understanding of how socioeconomic factors affect land use (Mena et al., 2006).

In terms of policy, it is important to highlight that in Sao Paulo state there is an Environmental Policy called “Green-Blue County Program”, established in 2007. The main objectives of this policy are to improve the environmental management efficiency and value society involvement at the county level. The project is voluntary and can be implemented by any county that is willing to comply with the Green Protocol. There are 10 Directives related to: 1-

sewage treatment, 2- garbage disposal; 3- riparian forests, 4- urban reforestation, 5- environmental education and sustainable housing, 7- water use, 8- air pollution, 9-environmental infrastructure for policy making and implementation and, 10 - environmental counseling.

As part of Activity 1 tasks, our group performed a series of analysis in intensively researched sites in two counties, Ipiguá and São José do Rio Preto (SJRP) in São Paulo State, Brazil, both dominated by sugar cane plantations. Our results show that pasture areas in SJRP went down from 71% in 1988 to 41% in 2008, having been replaced by forests (14 %), settlements (about 8 %) and sugar cane (8 %). In Ipiguá, in 1988, 68% of the county landscape was covered by pasture and 17% by forests. Twenty years later, pasture areas had decreased by 4% and forests by 3% of the previous area, while sugar cane had gained 6.6 %. The increase in forest area in SJRP was related to the "Green County Project", an environmental policy established by the São Paulo State government in 2007. The main objective of this policy is to improve the environmental management efficiency and value society involvement at the county level. While SJRP had joined this program and already has a green seal due to the implementation of restoration laws and practices, Ipiguá has not joined.

These results show the potential role of an environmental public policy which can be responsible for the restoration and preservation of ecosystems goods and services. To investigate if a) this pattern is found in other counties where ethanol sugar-cane is expanding and b) identify economic and/or social drivers or indicators that can be associated with environmental and agricultural changes. Therefore, the main goal of this last phase of our research was to verify if this environmental policy (Green-Blue County Program) has been strong enough to avoid deforestation caused by sugarcane expansion. The tasks developed to achieve this goal we analyzed the relationship among forest cover change and economic indices between 2005 and 2009 in green and non-green counties.

## **2- METHODOLOGICAL APPROACH**

The effort on documenting the patterns and pace of deforestation and identifying the drivers of forest loss can be divided into four main categories (Laurence et al., 2002):

§ Remote-sensing studies that quantify rates and spatial extent of forest clearance;

- § Conservation gap analyses that assess the impacts of deforestation on different vegetation types;
- § Evaluation of the effects of government policies and development activities on deforestation. For example, the relationship between internationally funded development projects, highway building, immigration, land speculation and deforestation in Brazilian Amazonia, the role of government policy and land-tenure conflicts in promoting environmental degradation
- § Modeling studies that attempt to identify the proximate causes of deforestation. Such studies underlay efforts to simulate possible future scenarios and evaluate proposed development schemes in the region

Building possible scenarios of land use change can be achieved using two main categories of models Mas et al (2004): (1) empirical models based on extrapolating patterns of change observed over the recent past, with a limited representation of the driving forces of these changes, and (2) simulation models based on the thorough understanding of change processes.

Model development describing land use/cover change processes is not trivial and poses many challenges due to the large number of driving factors, and the complexity of the innumerable interactions among human decisions and natural processes leading to emergent properties. Moreover, as several studies have already shown, forest clearing can't be treated as the result of the sum of the effects of each factor in an independent form but rather need to be represented as a combination of them. Therefore, better results can be expected from artificial neural networks (ANNs), once they are able to directly take into account any non-linear complex relationship between the explicative variables and deforestation.

For instance, a comparison of five modeling techniques (generalized additive models, classification and regression trees, multi-variate adaptive regression splines, artificial neural networks and simple linear model used as reference), for forest characteristics mapping in the Interior Western United States, showed that there was little appreciable difference among them when using real data. To understand the spatial and temporal distribution of land use and land cover change, several others studies have been developed using uni-variate regression (Chen et al., 2010), bivariate regression analysis (Sambrook et al. 2010) and multiple linear regression (Hayes et al., 2008; Hayes and Cohen, 2007).

In the particular case of analyzing the relationship among public policies and forest cover change, a linear regression model was developed to estimate the effect of local government policies on the preservation of tree canopy in Greater Atlanta region (Hill et al., 2010). To identify which policy is the best at preserving or increasing urban forests, the following linear regression model was applied:

$$\begin{aligned} \text{canopy}_i = & \beta + \text{treeord}_i \beta_{\text{treeord}} + \text{mgt}_i \beta_{\text{mgt}} + \text{pop}_i \beta_{\text{pop}} \\ & + \text{comm}_i \beta_{\text{comm}} + \text{IS}_i \beta_{\text{IS}} + \text{ex}_i \beta_{\text{ex}} + \text{inhibit}_i \beta_{\text{inhibit}} \\ & + \text{landuse}_i \beta_{\text{landuse}} + \text{clauses}_i \beta_{\text{clauses}} + \text{zoning}_i \beta_{\text{zoning}} \\ & + \text{board}_i \beta_{\text{board}} + \text{develreg}_i \beta_{\text{develreg}} + \text{CCdum}_i \beta_{\text{CCdum}} \\ & + \varepsilon_i \end{aligned}$$

Where:

*Canopy* = Change in the percent of tree canopy cover, 1991–2001

*IS* = Change in the percent impervious surface, 1991–2001

*Landuse* = Weighted index of land use types: residential (.50), commercial (.25), industrial (.15), other (1.0)

*Pop* = Change in the percent population, 1990–2000

*ex* = Index of the number of exemplary quality growth examples

*mgt* = County has established a tree care entity

*comm.* = Index of mediums used by county to communicate about trees

*Zoning* = Index of quality growth and tree canopy efforts exhibited in zoning (0–20)

*develreg* = Degree of development regulation (none, somewhat, and significant regulation)

*Inhibit* = Index of inhibitors faced by a county that prevent meeting tree goals

*Board* = County has established a tree board

*treeord* = County has established a tree ordinance

*Clauses* = Index of tree preserving clauses in tree ordinance

*CCdum* = Dummy variable defining Cobb and Clayton County as one, otherwise zero.

Betas's are parameters to be estimated and the subscript *i* refers to the county, which is our level of observation. Endogeneity to certain variables was corrected by a generalized method of moments (Greene, 2008). The instruments used included data on population, percent of urban population, age, income, and college education levels in each county.

However, population growth is not the only factor driving deforestation, specially in the tropics (Geist and Labin, 2001). Other factors, such as favorable credit policies for cattle ranchers; inappropriate land tenure arrangements; road construction and associated frontier development and/or resettlement schemes; land speculation, mining and timber activities can play also an important role as explanatory variables (Sambrook et al., 2010). For instance, in the amazon region, human-demographic variables (population density, urban population and rural population), physical accessibility to forests (highways, roads, navigable rivers), and land-use suitability for human occupation and agriculture (climatic and soil characteristics), have been identified as important drivers of deforestation (Alves et al., 2010; Ballester et al., 2003; XXX) .

In urban forests, management, employee training, education, and financial assistance are crucial for the operation of successful tree protection policies are factors to be consider (ODF, 2004; Elmendorf et al., 2003; Hill et al., 2010).

### **3. THE GREEN-BLUE COUNTY PROGRAM**

The Green-Blue County Program was launched in 2007 by the government of Sao Paulo state with the aim of decentralizing environmental policy and gain efficiencies in environmental management. The Program is voluntary, and occurs from signing a "Memorandum of Understanding" which proposes 10 Environmental Policies that address priority environmental issues to be developed. According to the official website of the program, the 10 Policies are:

- 1. *Treated Sewage:*** management of 100% of the municipal sewage by 2010, or in case of being financially unviable, sign a commitment agreement with the Secretary of State for the Environment, pledging to carry the service until the end of 2014
- 2. *Minimum Waste:*** Guarantee correct solid waste collection, recycling and disposal to the garbage generated in the county.
- 3. *Riparian Forest:*** Participate in partnership with other public agencies and society for recovery of riparian areas, identifying areas, developing municipal projects and enabling the implementation of the projects.

4. **Urban Afforestation:** Increase the urban green areas, diversifying the use of planted species (especially native and fruit species). Ensure the maintenance of these urban green areas and the supply of seeds for the forestation of degraded areas.
5. **Environmental education:** Develop an environmental education program, promoting public awareness regarding the actions of the environmental agenda. Participate in initiatives of the Secretary of State for the Environment.
6. **Sustainable Housing:** Define sustainability criteria in the expedition of the construction permits, restricting the use of native timber (mainly coming from the Amazon region) and promoting the development and application of technologies to saving natural resources.
7. **Water Use:** Discourage excessive water consumption and support mechanisms for charging for water use in its watershed. Promote and integrate the work of the Watershed Committees.
8. **Air pollution:** Assist the government to control air pollution (especially related to vehicle emissions of black smoke from diesel engines). Participate in other initiatives in the defense of air quality.
9. **Environmental structure:** Constitute an executive board responsible for environmental policy in the county. In cities with more than 100.000 inhabitants, establish a Secretariat for the Environment and ensure the training of the staff that composes this Secretariat.
10. **Environment Council:** Constitute an advisory and deliberative board, ensuring the participation of the community in local environmental management policy agenda.

There are another two aspects of these directives that need especial attention since can they have a positive impact on the county forest area. While directive number 3 regulates riparian forest, directive number 4 deals with urban forest. Therefore, we included them in this report in order to identify the role of each one on the Program and also on forest cover.

A weighed equation, the Evaluation Environmental Index (Eq. 1), is applied to rank the level of achievement of the ten directives.

$$EEI = \sum IDi + \sum PROi - PP \quad (\text{Eq. 1})$$

Where:

$i = \text{Environmental Directive } (i = 1 \text{ to } 10);$

$\sum IDi = \text{sum of the Environmental Directive ,}$

$\sum PROi = \text{sum of the pro active initiatives defined as weights presented in Table 1}$

*PP = any county environmental passive*

**Table 1.** *Pro active initiatives weights presented of each Directive of the Green-blue County Programm (SP, Brazil).*

Directive Number	Directive objective	Weight
1	Treated Sewage	1.2
2	Minimum Waste	1.2
3	<i>Riparian Forest</i>	0.8
4	Urban Afforestation:	0.5
5	Environmental education	1.2
6	Sustainable Housing	0.5
7	Water Use	0.5
8	Air pollution	0.5
9	Environmental structure	0.8
10	Environment Council	0.8

A County can be certified as Green-Blue when its EEI reaches a value of at least 80. Another 5 criteria need to be meet for the certification:

- I – establish by law a Municipal Environmental Council;
- II - establish by law and implement an environmental executive structure;

- III – obtain a grade equal to or higher than 6 for the Residues Disposal Index;
- IV - obtain a grade equal to or higher than 6 for the sewage treatment and
- V – Score points for all directives.

#### 4. METHODS

The sugarcane expansion and other socioeconomics variables have brought serious land use changes to the counties located in the Sao Paulo state. In this study, forest areas in 28 counties were used as dependent variable in the multiple linear regression (MLR), while the sugarcane area and other socioeconomics and agricultural variables were taken as independent variables. Figure 1 illustrates the steps involved in the method, starting by a site selection, followed by the socioeconomic and agricultural indicators selection, data collection and model development.

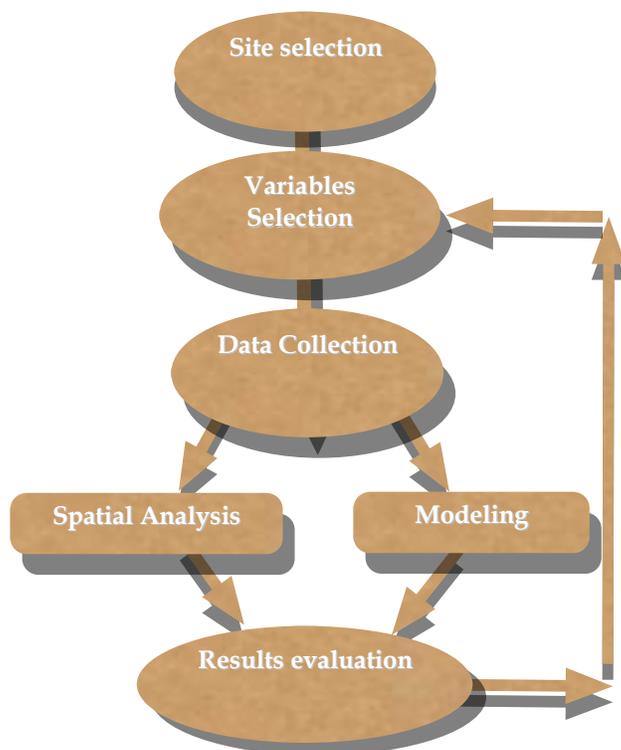


Figure 1. Methodological steps

### **a. Site selection**

We were selected a total of 28 paired counties in São Paulo State, Brazil: 13 “green” and 15 “non-green” (Figure 2). In this site selection, it were adopted tree criteria:

- a) counties must be geographically located in a region of sugar cane expansion;
- b) each green selected county shares a political boundary with at least one selected non-green county;
- c) four counties where sugar cane was already one of the major agricultural commodities where selected as controls.

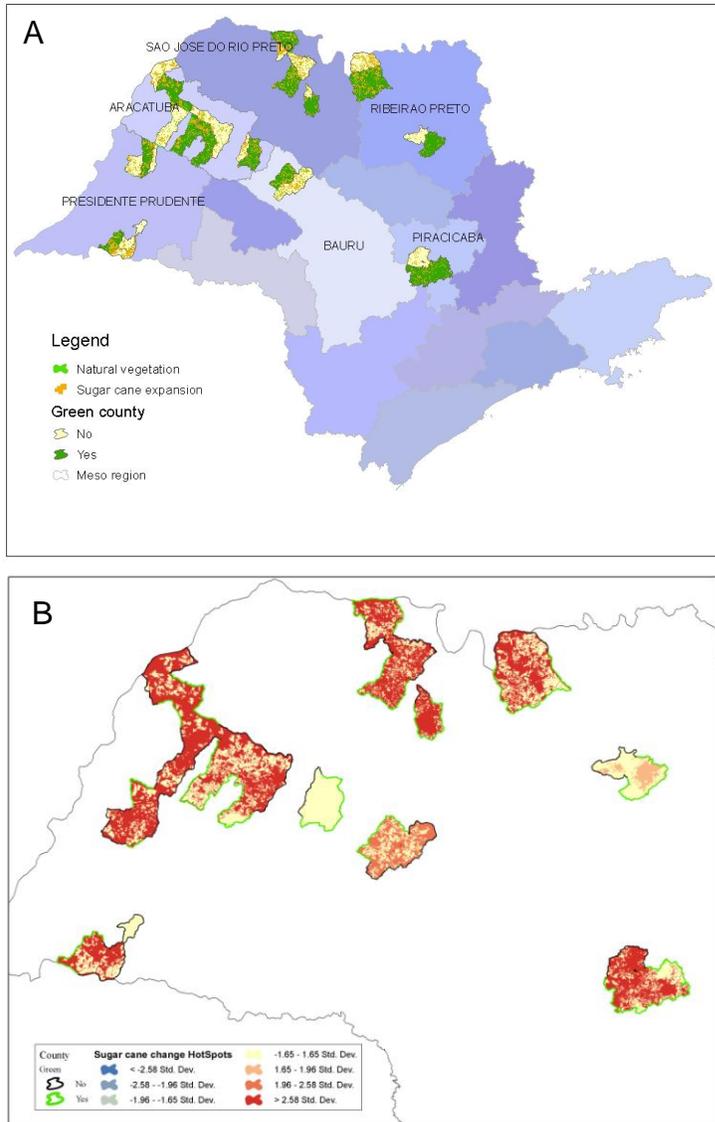


Figure 2. A- Study area: location of 28 selected counties in São Paulo State (Brazil) and B- sugar cane cover at each county (Source Canasat, INPE, 2011)

### **b. Definition of Economic, social and agricultural indicators**

The dependent variable of the multiple linear regression (MLR) developed in this study was the change in percent of 28-county forest area between 2005 and 2009. These data were provided by the São Paulo State Forest Institute.

As explanatory or independent variables, were taken some important indicators frequently suggested by the literature as determinants of land use and forest area. These variables were divided in economic, social and agricultural groups of indicators (Table 2). The main sources of secondary data were the Geography and Statistics Brazilian Institute (IBGE) and the State System for Data Analysis Foundation (SEADE).

Table 2 - Economic, social and agricultural indicators

<b>Group</b>	<b>Indicators</b>	<b>Source / Database</b>
Economic	<sup>1</sup> Gross Domestic Product – agriculture <sup>2</sup> Gross Domestic Product – industry <sup>3</sup> Gross Domestic Product – services <sup>4</sup> Gross Domestic Product per capita <sup>5</sup> County expenses in agriculture <sup>6</sup> Total county expenses in Environmental management	<sup>1, 2, 3, 4</sup> SEADE, Product and income <sup>5, 6</sup> SEADE, County Public Finances
Social	<sup>1</sup> Population Density <sup>2</sup> Healthy facilities - Bed in public hospitals <sup>3</sup> Scholarship – Education level	<sup>1</sup> SEADE - Population and vital statistics <sup>2</sup> SEADE - Health <sup>3</sup> SEADE and IBGE - Education
Agricultural	1- Livestock - Number of cattle 2- Sugarcane - production, area planted and production value 3- Number of productive properties 4- Rural credit	<sup>1,2</sup> SEADE, Agriculture, livestock and planted forest and IBGE, County Livestock <sup>3,4</sup> SEADE, Agriculture, livestock and planted forest

Also, data on sugarcane cover maps were obtained from *CanaSat* Project (INPE, 2011), that uses satellite images to identify and map the area cultivated with sugarcane harvest.

Finally, “green certification” is a binary variable that accounts for whether or not a county had obtained acknowledgment from the “Green County Project”.

### **c. Spatial and temporal analysis**

To characterize the study area, we performed a spatial analysis of physical, biotic and human limiting factors for sugar cane expansion, including topographic and soil limitations, legal limitation and presence of infrastructure. All socioeconomic indicators were also analyzed to understand general trends.

#### **d. Data processing and the model**

The method to process data was based on Chen et al. (2010), and the econometric model developed was based on Hill et al. (2010) and Hayes et al. (2008). In this study, data processing followed the steps illustrated below. First of all, we developed a Multiple Linear Regression (MLR), considering 14 explanatory socioeconomic and environmental variables; the majority of them are suggested by similar studies as significant variables to explain the forest cover area and the land use change (Eq. 2). Since the results were not satisfactory, we developed 14 Simple Linear Regression (SLR), processing each of 14-independent variable in order to capture their respective impact on the dependent variable (Eq. 3). In both cases, the variables were measured by their percent change between 2005 and 2009.

$$Forest_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots + \beta_k X_{ki} + \varepsilon_i \quad (\text{Eq. 2})$$

$$Forest_i = \text{Change in the percent of forest cover, 2005-2009 } (i = 1 \text{ to } 28\text{-county}) \quad (\text{Eq. 3})$$

Where:

$X_1$  = Populaion density

$X_2$  = Healthy facilities – Number of beds in Public Hospitals

$X_3$  = Number of productive properties

$X_4$  = Rural Credit

$X_5$  = County expenses with Agriculture

$X_6$  = County expenses with environmental management

$X_7$  = GDP – Agriculture

$X_8$  = GDP – Industry

$X_i$  = Change in the percent of Explanatory variables, 2005-2009 ( $k = 1$  to 14 variables)

## 5. RESULTS AND DISCUSSION

### 5.1. Multiple Regression Model (MRM)

Table 3 presents the results of the Multiple Regression Model obtained using all chosen explanatory variables. Overall, the independent variables explained 65.3 % of the observed variability on forest cover. However, these results show that the MRM implemented had no consistency for explaining the effectiveness of the Green-Blue County had on forest cover and socioeconomic benefits. Only the number of enrolled students in schools presented a statistical significant relation for a 95%. ( $\alpha = 0,05$ ) of confidence.

Table 3 - Multiple Regression Model of forest cover and socio-economic variables for 28 selected counties of Sao Paulo State.

Variable	Expected Effect	$\beta$	Standard Deviation	T Statistic	Level of Significance
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Constant		-0,1908	0,3976	-0,48	0,6394
Population Density	(-)	-0,5680	4,8759	-0,12	0,9090
Number of Public hospital beds	(+)	0,3044	0,4859	0,63	0,5419
Number of productive properties	(-)	1,4210	1,2758	1,11	0,2855
Rural Credit	(-/+)	0,1880	0,1158	1,62	0,1286
Expenses with Agriculture	(-)	0,0075	0,0047	1,60	0,1335
Expenses with Environmental Management	(+)	0,1899	0,8330	0,23	0,8233
Value added by agriculture and livestock	(-)	1,0484	0,6030	1,74	0,1057
Value added by Industry	(+)	0,1968	0,2579	0,76	0,4590
Value added by Services	(+)	1,9611	1,2005	1,63	0,1263
PIB Per capita	(+)	-1,5301	1,2430	-1,23	0,2401
Scholarship – Education level	(+)	-2,6436	0,9709	-2,72	0,0174
Number of Cows	(-)	0,2441	0,8483	0,29	0,7781
Sugar cane harvested area	(-)	0,0106	0,0081	1,31	0,2142
Value added by Sugar cane production	(-)	-0,0206	0,0311	-0,66	0,5192

$R^2 = 0,6532$

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Of the total 14 analyzed variables, only seven presented the expected results in terms of positive or negative effects on forest cover. For instance, we expected that as the county level of education increased, a higher level of environmental conscience would be achieved by the population and government, leading to increased forest cover in the county. This hypothesis was not confirmed.

## 5.2. Simple Linear Regression Model

The Simple Linear Regression, using one predictive variable at each time showed some different results. Over all, four variables were statistically significant to explain the observed changes in forest cover: Value added by Sugar cane production, Value added by agriculture and livestock, number of Cows and Sugar cane harvested area. Each variable explained less than 20% of the observed variability (Table 4).

Table 4. – Simple Linear Regression results of forest cover and socio-economic variables for 28 selected counties of Sao Paulo State.

Variable	Expected	Std		Stat T	Sig.	R <sup>2</sup>
	Effect	□	Dev			
Population Density	(-)	-0.4030	3.4662	-0.12	0.9100	0.0005
Number of Public hospital beds	(+)	0.2278	0.4532	0.50	0.6195	0.0096
Number of productive properties	(-)	-0.1098	0.9169	-0.12	0.9056	0.0006
Rural Credit	(-/+)	0.0535	0.0799	0.67	0.5091	0.0169
Expenses with Agriculture	(-)	0.0040	0.0041	0.99	0.3300	0.0364
Expenses with Environmental Management	(+)	-0.4539	0.6338	-0.72	0.4800	0.0193
Value added by agriculture and livestock	(-)	0.5982	0.2570	2.33	0.0300	0.1725
Value added by Industry	(+)	0.0204	0.0792	0.26	0.8000	0.0025
Value added by Services	(+)	0.3776	0.4358	0.87	0.3900	0.0281
PIB Per capita	(+)	0.1095	0.2386	0.46	0.6500	0.0080
Scholarship – Education level	(+)	-1.3982	0.9377	-1.49	0.1500	0.0788
Number of Cows	(-)	1.2184	0.6405	1.90	0.0700	0.1222
Sugar cane harvested area	(-)	0.0126	0.0066	1.90	0.0700	0.1221
Value added by Sugar cane production	(-)	0.0400	0.0148	2.55	0.0200	0.1999

### 5.3. Other simulations and tested models

To verify if the low level of significance of the applied models was the result of a untypical event on the socio-economic and forest cover data, e.g. in 2005 or 2009 some point event could have result in a change of trend influencing the data sets, the same models were tested for a broader larger period of time. Therefore, MLR and SLR models were re-run using

data for the same 14 variables, spanning a time scale of 6 years, from 2003 to 2009. Data for 2005 and 2009 were inserted into the model as averages from 2003, 2004 and 2005 and 2007, 2008 and 2009, respectively. The results from these simulations confirmed our previous results, there was still no consistency on describing the dependent variable. Only 40% of the observed variability was explained by the multiple regression model (Table 5), while the simple regression analysis showed no change in terms of the previous results (Table 6), but with a lower level of significance ( $R^2 < 15\%$ ).

Exponential and logarithmic models were also tested with even less satisfactory results, indicating that the variables selected are not enough to describe, or even correlated to forest cover changes. Collection of more detailed primary data it's necessary to calibrate the models.

Tabela 7 – Second Multiple Regression Model of forest cover and socio-economic variables for 28 selected counties of Sao Paulo State.

Variable	$\beta$	Std Dev	Stat T	Sig.
Population Density	0,1101	0,5725	0,19	0,8505
Number of Public hospital beds	1,4461	5,8833	0,25	0,8097
Number of productive properties	-0,0770	0,9786	-0,08	0,9385

Rural Credit	0,6679	2,0263	0,33	0,7469
Expenses with Agriculture	0,0753	0,1129	0,67	0,5165
Expenses with Environmental Management	0,0176	0,0305	0,58	0,5734
Value added by agriculture and livestock	0,0009	0,0179	0,05	0,9625
Value added by Industry	0,0371	0,7052	0,05	0,9589
Value added by Services	-0,0278	0,6294	-0,04	0,9654
PIB Per capita	0,2044	1,4591	0,14	0,8908
Scholarship – Education level	0,1883	1,7785	0,11	0,9173
Cows	-1,2728	2,6023	-0,49	0,6329
Sugar cane harvested area	0,9243	1,3137	0,70	0,4941
Value added by Sugar cane production	0,0247	0,0196	1,26	0,2313
Population Density	0,0256	0,0498	0,51	0,6164
R <sup>2</sup> = 0,4060				

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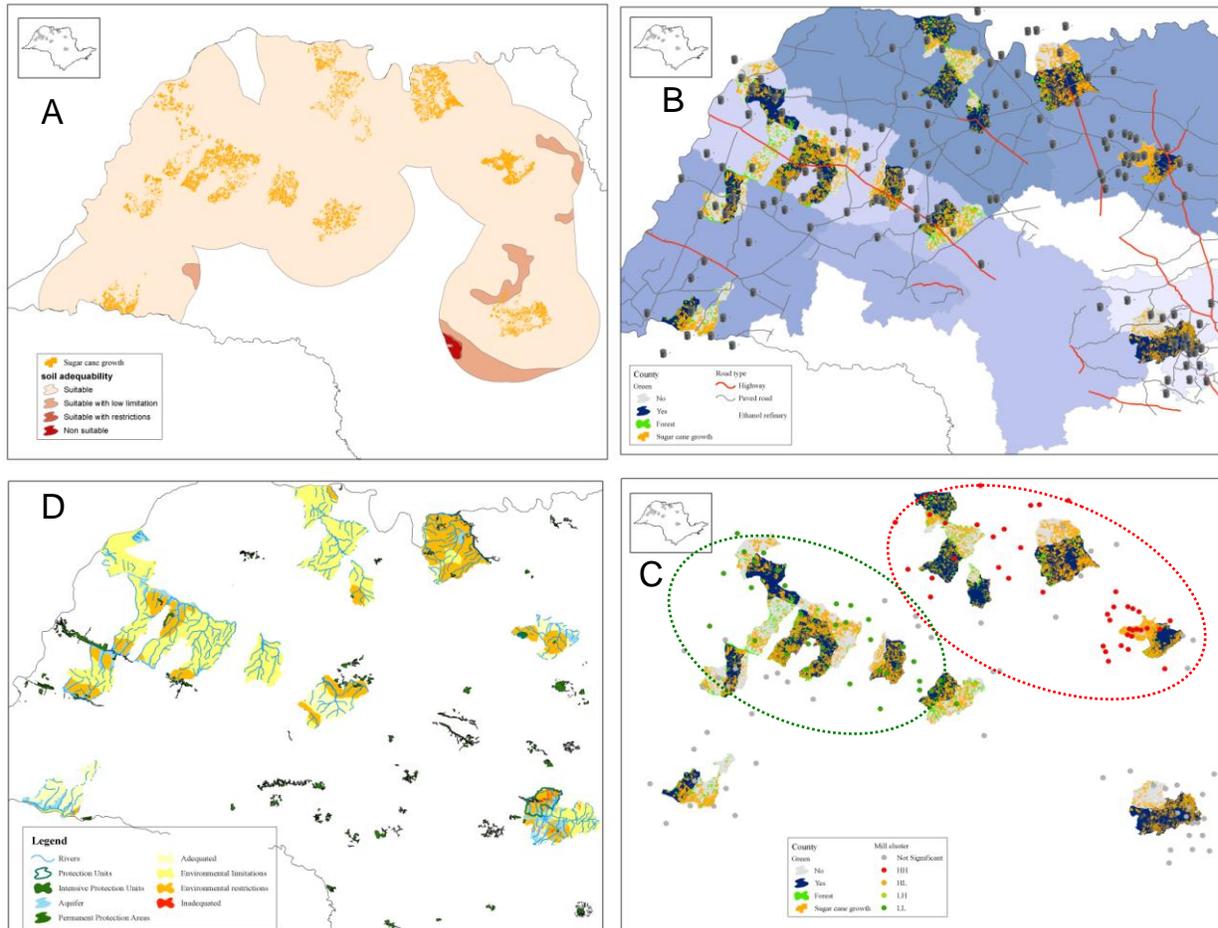
Table 8 – Second Simple Linear Regression results of forest cover and socio-economic variables for 28 selected counties of Sao Paulo State.

Variable	$\beta$	Std Dev	Stat T	Sig.	R <sup>2</sup>
Population Density	-0,3885	3,4643	-0,11	0,9116	0,0005
Number of Public hospital beds	-0,5375	0,5851	-0,92	0,3667	0,0314
Number of productive properties	0,6769	1,3089	0,52	0,6094	0,0102
Rural Credit	0,0333	0,0800	0,42	0,6809	0,0066

Expenses with Agriculture	0,0183	0,0185	0,99	0,3315	0,0363
Expenses with Environmental Management	0,0100	0,0130	0,77	0,4481	0,0223
Value added by agriculture and livestock	0,1441	0,1961	0,73	0,4692	0,0203
Value added by Industry	0,0680	0,1390	0,49	0,6285	0,0091
Value added by Services	0,2592	0,4324	0,60	0,5541	0,0136
PIB Per capita	0,1810	0,2691	0,67	0,5071	0,0171
Schollarship – Education level	-1,0181	1,6135	-0,63	0,5335	0,0151
Cows	1,1366	0,7814	1,45	0,1578	0,0753
Sugar cane harvested area	0,0251	0,0123	2,04	0,0518	0,1378
Value added by Sugar cane production	0,0388	0,0184	2,11	0,0450	0,1457

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Other factors, such as physical, biotic and human constrains need also be taken into account. Figure 3 presents the maps of soil sustainability (Sao Paulo, 2010), roads, distilleries and legal constrains (conservation units) and sugar cane expansion clusters in the study area. In general, soils present no restriction for sugar cane plantation. Of the total amount of 373,244 ha of sugar cane expansion in 4 years (2005 to 2009), less than 0.2 % of sugar cane expansion between 2005 and 2009 was on low limited soils. Infrastructure is well developed in the region, 6770 km of roads and 130 ethanol plants, forming two clear clusters. The main constrain for sugar cane expansion was represented by legal limitations, 48 % of the study area was within the limits of a Protection Area or Conservation Units where agricultural and cattle raising



**figure 3.** A- Soil sustainability (Sao Paulo, 2010), B - roads, C) distilleries (ANA, 2010) and legal constrains (conservation units, Sao Paulo, 2010) and sugar cane (Canasat) expansion clusters in the study area.

On average, more intensive sugar cane growth and pasture replacement was found at Green-Blue Counties, where annual and perennial crops cultivated area also decrease (Figure 4), while forest cover presented a growth. At non-green counties sugar cane growth was also associated with pasture cover decrease, but annual and perennial crops showed an increase and forest losses were more intense and common. On average, Green-Blue counties presented higher and increasing rural credit, and more economic value (R\$) was added by sugar cane. Simultaneously, livestock had a smaller contribution in their economy when compared to the non-green counties. Also, Green-Blue counties presented lower losses in term of values added

from agricultural activities, a larger increase in PIB per capita (R\$) and more economic value (R\$) added by industry and services.

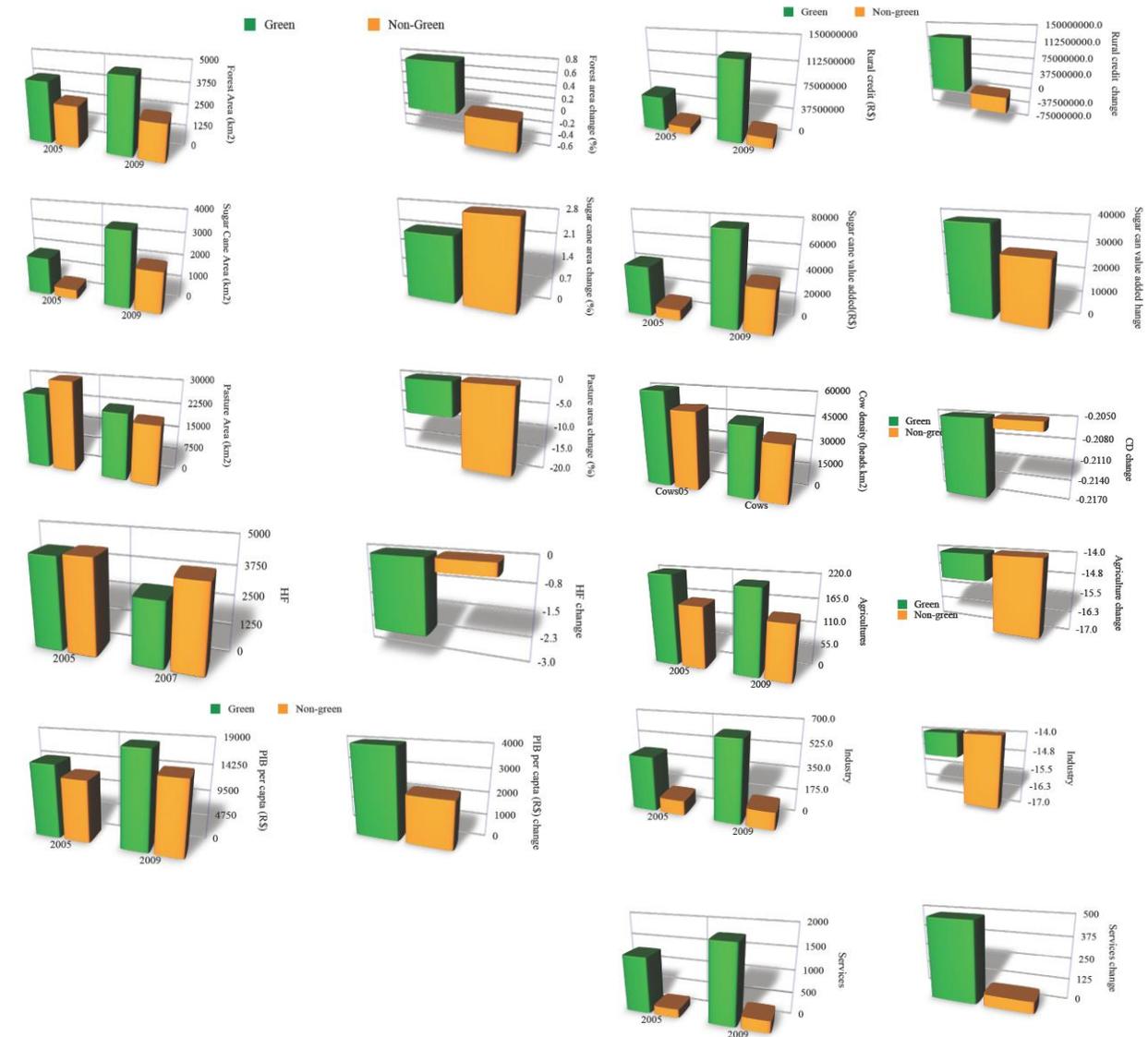


Figure 4. Average values of 14 socioeconomic indices for 28 Green-Blue and Non-Green-Blue counties in São Paulo State (Brazil).

Moreover, forest preservation and restoration in Green-Blue counties was quantitatively higher and more consistent indicating that the program is producing in most instances the expected results (Figure 5). However, there are still inconsistencies in the indices. For instance, some Green-Blue counties showed a decrease in forest area, but still got high grades, of the 12

evaluated green counties, 02 presented a forest area decrease of 25% and 83%, respectively. The opposite situation was also verified for 4 non-green counties.

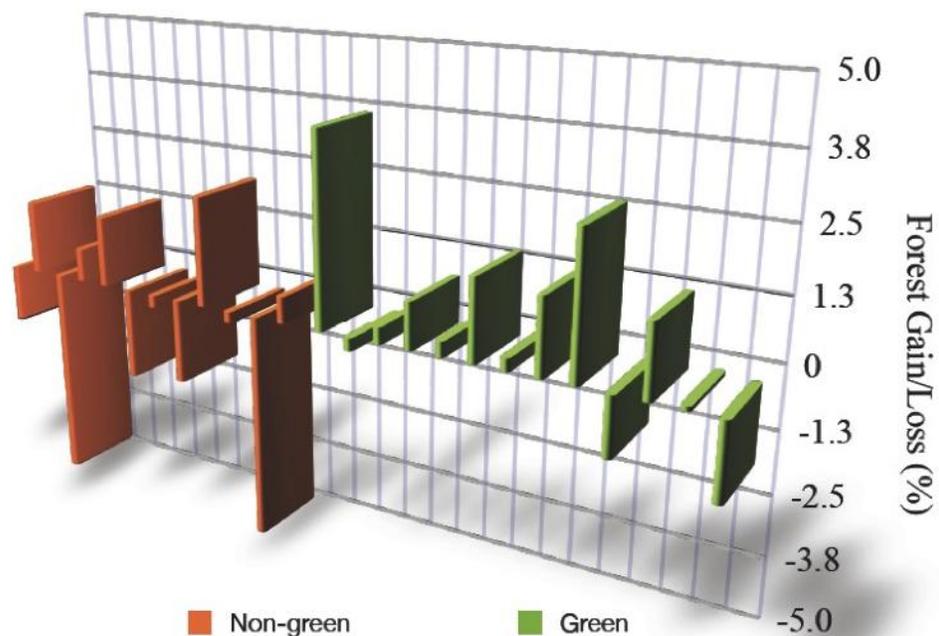


Figure 5. Forest cover gain and losses for 28 Green-Blue and Non-Green-Blue counties in São Paulo State (Brazil).

## 6- Concluding remarks

As the models results, this evaluation indicates that other factors besides the socio-economic variables consider in this study are driving land cover and land use change, and therefore forest cover. Other public policies, designed specifically for forest restoration and preservation, or even governmental supervision can have important impacts on this variable than a broader state program such as the Green-blue county.

As mentioned in the report before, it is important to highlight some aspects of the Green-Blue Program can have reflexes on the model sensitivity to detect land cover changes:

1. The program consists of 10 policies, of which only two are related to actions that interfere in forest cover: "Policy 3 - Recovery of Riparian Vegetation" and "Policy 4 - Urban Tree;
2. The final score for each county is a weighted, with a different value assigned to each Policy. The weights of Policies 3 and 4 (0.8 and 0.5, respectively) indicate that recovery of riparian and urban forest forestry are not priority in the program;
3. Annually, the evaluation criteria for each policy had small alterations, which may hinder problems for a temporal evaluation of the scores assigned to each county;
4. The program is relatively recent, and their results are still not enough to assess its impact in terms of vegetation cover.

Also. It is important to highlight the fact that in Brazil there is specific legislation regulating the permanent preservation areas (in which riparian vegetation is included), and the legal reserve in rural properties. Therefore, if demands for riparian forested areas is related to the presence of water bodies and rivers in the county, a more effective regional policy should take this aspect into account. A first step would be, for example, define actually comparable indicators, since evaluating the increase of forest area may not be the best predictor if forest cover natural condition is different among the counties. Any policy must have goals, targets and indicators, so that a periodic evaluation of its results can be performed, regardless of their scope (local, municipal, regional, state or national). Furthermore, it's interesting to establish a monitoring methodology that is realistic and at the same time, relatively easy to apply, so that the survey and data verification does not constitute an issue for the program's success. Thus in the case of public policies involving riparian forests for example, an interesting indicator that could

be subject to regular monitoring is the total riparian area or legal reserve in each municipality that have been recovered or is in recovery. As for areas that go beyond these "legal requirements", indicators that relate forest areas with population or total area of the municipality could also be interesting.

Other public policies can also provide economic incentives for planting of forest areas. One example is the program involving partnerships between the public and private sectors for "payment for environmental services". There are already several of these programs in Brazil, where farmers receive an economic compensation for protecting water resources by maintaining forest cover at headwaters. In urban areas, afforestation, introduction of green areas and recreational parks can be places of public policy actions. Tree planting programs involving population, environmental education and theme parties can also be part of such policies.

Finally, this study "pilot" study, involving a sample of 28 counties in Sao Paulo State also indicates some limitations and the need for advances in a number of areas to improve our understanding of the relationship between the behavior of land use and forest cover changes. Among the limitations and the necessary advances, we can mention:

1. Availability and characteristics of secondary data: secondary data is poor, and it's necessary to collect it from different sources and years, which may negatively impact model results. The lack of statistical analysis on more appropriate databases and inconsistencies in recording data also need to be addressed

2. Primary data collection: it can be very useful to incorporate data collected from local governments at the county level. Such data might relate, for example, the local actions of the county that have been conducted and / or planned for engagement and public concern over the issue, private sector initiatives that can be observed, the profile of farmers and the municipality his stance on the Forest Code, the main existing cultures, among others.

3. Qualitative analysis:

In addition to regression models, it is interesting from the survey of primary information, conduct a qualitative analysis of both counties. Often, an approximation of the local can be more effective in terms of contribution to the understanding of drivers of land use change at the

county level that a mathematical model, since it may involve qualitative variables. A qualitative analysis should be included to support or enhance the understanding from the regression models.

4. Sample of municipalities: apart from data limitations, size and profile of the sample selected in this study may have influenced the results. A more detailed study should seek to broaden the sample size in order to minimize the likelihood of distortions due to sample characteristics.

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