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# Land Changes Fostering Atlantic Forest Transition in Brazil: Evidence from the Paraíba Valley

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The Atlantic Forest biome has only 13 percent of its pristine vegetation cover left. This article analyzes the consequences of land changes on forest cover in the Paraíba Valley, São Paulo state, Brazil, from 1985 to 2011. Multitemporal satellite image classifications were carried out to map eight land use and land cover classes. The forest cover increased from 2,696 km<sup>2</sup> in 1985 to 4,704 km<sup>2</sup> in 2011, mostly over areas of degraded pastures. The highest rates of afforestation were observed within protected areas around eucalyptus plantations. On the other hand, deforestation processes were concentrated on areas covered by secondary forests. Socioeconomic changes taking place in particular Brazilian settings, such as industrialization and agricultural modernization, allied to the Paraíba Valley's natural biophysical constraints for agricultural production, have led the region to experience a remarkable case of forest transition. **Key Words: land abandonment, Landsat, regional environmental change, secondary succession, socioeconomic changes.** 

大西洋森林生物群落,仅存有原始植被覆盖的百分之十三。本文分析巴西圣保罗的帕拉伊巴河谷自 1985 年至 2011 年 间,森林植被的土地变迁之后果。本文进行多时相卫星影像分类,以绘製八种土地使用和土地植被的类别。森林植被自 1985 年的两千六百九十六平方公里,增加至 2011 年的四千七百零四平方公里,且多半是在退化的放牧地区中。最高 比例的造林,是在尤加利树植栽附近的保育地区中被发现。另一方面而言,森林砍伐过程则集中于由原始次生林所覆盖 的区域中。在特定的巴西脉络中发生的社会经济变迁,例如工业化和农业现代化,结合帕拉伊巴河谷之于农业生产的自 然生物物理限制,导致了该区域经历了可观的森林变迁案例。关键词:土地退耕,土地使用卫星影像,区域环境变迁,

# 次生演替,社会经济变迁。

Solamente queda en pie el 13 por ciento de la cubierta de vegetación prístina en el bioma del Bosque Atlántico. Este artículo analiza las consecuencias de los cambios de la tierra sobre la cubierta boscosa del Valle de Paraíba, en el estado de São Paulo, Brasil, de 1985 a 2011. Se efectuaron clasificaciones de imágenes satelitales multitemporales para cartografiar ocho clases de uso del suelo y cobertura de la tierra. La cobertura boscosa se incrementó de 2.696 km<sup>2</sup> en 1985 a 4.704 km<sup>2</sup> en 2011, principalmente sobre áreas de pasturas deterioradas. Las tasas más altas de reforestación se observaron dentro de áreas protegidas alrededor de plantaciones de eucaliptos. Por otra parte, los procesos de deforestación se concentraron en áreas cubiertas con bosques secundarios. Los cambios socioeconómicos que están dándose en ciertos escenarios brasileños, tales como industrialización y modernización agrícola, sumados a los limitantes biofísicos naturales para la producción agrícola en el Valle de Paraíba, han llevado la región a experimentar un notable caso de transición forestal. **Palabras clave: abandono de la tierra, Landsat, cambio ambiental regional, sucesión secundaria, cambios socioeconómicos.** 

L and use and land cover changes result from a complex interaction of biophysical and human dimensions (Moran and Ostrom 2005; Caldas et al. 2013). Proximate causes are human actions that directly affect those changes (Geist and Lambin 2002). Examples include agricultural expansion, wood extraction, and urban development (Kaimowitz and Angelsen 1998; Caldas et al. 2007; Pacheco and Poccard-Chapuis 2012; Caldas et al. 2013). Several studies emphasize the importance of multitemporal image classification to estimate land use and land cover

changes and to quantify the human impacts on landscape structure (Foley et al. 2005; Lu et al. 2005; Moran and Ostrom 2005; Teixeira et al. 2009; Lira et al. 2012; Vaca et al. 2012; Lu et al. 2013).

Regional studies of forest cover in the Atlantic forest biome indicate periods of slight recovery followed by deforestation without a consistent trajectory of forest regrowth (Teixeira et al. 2009; Freitas, Hawbaker, and Metzger 2010; Lira et al. 2012). Different deforestation rates were observed for the Brazilian states in this biome, indicating a general trend of decline followed by the stabilization of forest remnants (Fundação SOS Mata Atlântica/INPE 2014). There are discrepancies, however, among data sets provided by different organizations and a lack of detailed information about processes of secondary succession (SS; Magnago et al. 2011), necessary to understand landscape dynamics (Farinaci and Batistella 2012).

The reversal trend in land cover for a given territory from a period of forest area net loss (e.g., deforestation) to a period of forest area net gain is known as forest transition (Rudel et al. 2005; Rudel, Schneider, and Uriarte 2010). The forest transition might not increase biodiversity in the short term due to the lower biological value of secondary forests and plantations compared to undisturbed forest ecosystems (Vaca et al. 2012). According to Queiroz et al. (2014), countries in Central and South America have reported positive effects of farmland abandonment on biodiversity. An analysis of ecological restoration projects across the globe indicates that restoration projects enhance provision of biodiversity by 44 percent compared to intact reference ecosystems (Benavas et al. 2009). The Brazilian Atlantic forest has been degraded for centuries and recent research on biodiversity reveals a decline in fauna leading the forest remnants to critical conservation levels (Galetti and Dirzo 2013; Dirzo et al. 2014). The Atlantic forest remnants, however, provide key ecosystem services influencing how water is channeled and stored in catchments, providing a source of medicinal plants, provisioning climate regulation, soil conservation, carbon storage, and aesthetic landscape values (Di Stasi et al. 2002; Silvano et al. 2005; Ditt et al. 2010; Paula, Costa, and Tabarelli 2011; Villela et al. 2012). The growth of new forest areas is a means to increase the core area of forest fragments and its connectivity, as well as to diminish edge effects, therefore enhancing biodiversity conservation values (Lira et al. 2012).

Atlantic forest remnants represent around 13 percent of its original vegetation cover (Fundação SOS Mata Atlântica/INPE 2014). This is the Brazilian biome with the highest number of extinct or endangered species as well as a biodiversity hotspot (Myers et al. 2000; Machado, Drummond, and Paglia 2008). The biome hosts the most developed regions of the country, concentrating around 60 percent of the human population (Fundação SOS Mata Atlântica/ INPE 2014).

In the 1950s, Brazil began an era of industrialization that was followed by the agricultural modernization period (Buainain et al. 2014; Silva 2015). These socioeconomic changes brought a variety of changes to the Brazilian population dynamics (e.g., massive rural-tourban migration), developed new agricultural areas (e.g., Brazilian Cerrado biome), promoted the adoption of land use mechanization, started the integration of Brazilian agro-production systems into international commodity markets, and marginalized unsuitable agricultural areas (Buainain et al. 2014). A vast literature in land use science has correlated land abandonment with unsuitable agricultural areas (e.g., steep slopes, low-fertility soils, etc.) or as consequences of socioeconomic factors, public policies, market demands, and land reforms (Dong et al. 2011; Alcantara et al. 2013).

São Paulo is the most developed state and concentrates 22 percent of the Brazilian population (Brazilian Institute of Geography and Statistics [IBGE] 2010). Approximately two thirds of the state's territory is part of the Atlantic forest biome (Fundação SOS Mata Atlântica/INPE 2014). São Paulo is a Brazilian agricultural power and contributed 20 percent of Brazil's gross domestic product (GDP) of the agricultural sector in 2013 (Barros et al. 2015). In the Paraíba Valley of São Paulo State, however, a region settled since the seventeenth century, a decrease in agricultural activities followed by farmland abandonment have been observed (Itani et al. 2011).

We hypothesize that forest transition is a major trend of land change in the Paraíba Valley in recent decades. This article critically assesses (1) land use and land cover for 1985, 1995, 2005, and 2011 calculated through a series of Landsat-5 Thematic Mapper (TM) images; (2) forest cover dynamics (afforestation and deforestation); and (3) major land use and land cover changes and their relation with socioeconomic factors.

# Study Area

The Paraíba Valley region, encompassed by the Paraíba do Sul watershed, spanning the states of São Paulo, Rio de Janeiro, and Minas Gerais in Brazil, has a fundamental role in water and energy supplies to more than 5 million inhabitants. The São Paulo portion of this basin, the study region (Figure 1), covers an area of more than 14,500 km<sup>2</sup>, supports a population of more than 2 million people, and represents 4.5 percent of the GDP of the State of São Paulo (Itani et al. 2011). The physical landscape is determined by two major geomorphological features: the mountainous areas with altitudes up to 2,000 m above sea level, and rolling hills with altitude variation around 200 m. The region is influenced by the Tropical Atlantic and Polar air masses that cause cold fronts, responsible for part of the annual rainfall of 1,700 mm on average, mainly concentrated between December and March (Rocha-Leão 2005).

In the past, coffee and milk production were the dominant economic activities. The rural economy has increasingly taken a back seat to industry in the region's GDP; consequently, the greatest increase in land use has been from eucalyptus plantations, mainly for pulp and paper exports (Itani et al. 2011). The landscape of the Paraíba Valley is predominantly composed of hilly terrain, considered a marginal area for agriculture (Silva 2015) and covered by pasturelands, patches of Atlantic forest remnants, eucalyptus plantations, and urban areas (Arguello et al. 2010).



Figure 1 The Paraíba Valley study region and the regional context. (Color figure available online.)

# Data and Methods

## Multitemporal Land Use and Land Cover Mapping

The data set consists of Landsat-5 Thematic Mapper (TM) imagery for 1985, 1994, 1995, 2005, and 2011 (Table 1), a set of forty-three RapidEye scenes, and fieldwork.

Image preprocessing started with registration and atmospheric correction using the Improved Dark-Object Subtraction (DOS2) method (Chavez 1988). Ancillary data sets included the Forest Inventory of the Natural Vegetation of São Paulo state (Instituto Florestal [IF] 2005) and the land use and land cover maps of São Paulo state in 1994, 2002, 2005 and 2008 (Funcate 2012). These maps were generated by visual interpretation of TM images including eight land use and land cover (LULC) classes (Table 2).

## Training Data

The RapidEye imagery of 2011 as well as fieldwork (2011 and 2012) data were used to define the training data for the supervised classification of 2011. The entire region is covered by a set of forty-three Rapid-Eye tiles (25 km  $\times$  25 km). The training data for the

eight classes (Table 2) were sampled in all RapidEye images using interpretation of high spatial resolution images. The fieldwork used in situ inspection to access ground truth information and validate the training data. To perform in situ inspection we randomly selected a subset of thirty samples for each LULC class. To validate the samples located in areas of difficult access such as steep slopes and forest fragments with restricted visiting conditions, we used the high spatial resolution imagery (RapidEye) as a surrogate for ground observation. The characterization of each LULC class followed the description presented in Table 2. We also took georeferenced pictures of each LULC class to assist with visual interpretation of high-resolution images in a computational environment. Based on the training data from 2011 (reference data), two steps were carried out to define the training data for the retrospective TM imagery: (1) spectral library and preliminary maps and (2) training data collection to the retrospective TM imagery.

First, from the training data from 2011, we built a spectral reference library using the TM spectral signatures for each LULC. The spectral library was used to classify the time series of TM images with the Spectral Angle Mapper (SAM). The SAM is a classification method for feature spectra based on a comparison of the spectral image with a reference spectrum (end

**Table 1**Landsat-5 thematic mapper imagery

Landsat-5 Thematic Mapper		Acquisition							
Scene 218/76	10/15/1985	08/24/1995	08/03/2005	09/09/2011					
Scene 219/76	11/07/1985	07/27/1994	04/20/2005	04/21/2011					

Classes	Description
Agriculture	Areas occupied by annual and perennial crops for food, feed, and fuel production (e.g., sugarcane, napier grass, rice, beans, and corn)
Water	Rivers, lakes, and reservoirs
Built-up areas	Urban and periurban areas, highways, industrial sites, and other built-up areas
Eucalyptus	Monocultural forest plantation with species of the <i>Eucalyptus</i> genus
Forest	Vegetation formations including stages of secondary succession (shrubland, young forest) and mature forest
Managed pasture	Areas used for grazing by cattle for milk and beef production with a predominance of grasses (e.g., molasses grass and <i>Brachiaria</i> sp.)
Degraded pasture	Areas with grasses cover, presence of shrubs, and other herbs, being used as pasture or abandoned
Bare soil	Exposed soils associated with agriculture and forestry activities, deforestation, or preparation for new built-up areas

Table 2 Land use and land cover classes used for the Paraíba Valley, São Paulo, Brazil

members or spectral libraries; Shafri, Suhaili, and Mansor 2007). The purpose of the classification by SAM was to generate preliminary maps to serve as support information to collect training data for each class in the retrospective imagery. This cascade classification procedure explores the existing temporal correlation between images acquired at different dates (Bruzzone and Cossu 2002).

The 2011 spectral reference data were then used to examine the field and spectral response patterns of the corresponding TM images in the time series to derive reference data for 1985, 1995, and 2005 LULC classes. Each sample used for training of 2011 images was checked against the TM images in the time series and with the preliminary maps generated by the SAM classifier, and thematic maps (ancillary data set) to ensure that the general LULC classes were the same. Based on this survey, the training data for 1985, 1995, and 2005 that did not match the corresponding LULC classes in 2011 were discarded from the reference data.

To evaluate the method's reliability, each set of training data for the retrospective imagery generated a spectral library from the reflectance information contained in the respective TM images. The mean and standard deviation were calculated from the spectral library data for six TM bands (1, 2, 3, 4, 5, 7) and for each year and mapping class. Thus, a two-tailed hypothesis test with a significance level of 1 percent was applied to evaluate the compatibility between the reflectance values of each class in the six bands with the average reflectance values of the same classes and bands in 2011 (reference data). The following hypotheses were defined:  $H_0$ :  $\mu = \theta$ (null hypothesis), and H<sub>1</sub>:  $\mu \neq \theta$  (alternative hypothesis), where  $\mu$  is the average reflectance value for a given class and band between the years 1985, 1995, and 2005 and  $\theta$  is the reflectance value of the same class and band in the year 2011.

#### Image Classification and Accuracy Assessment

Based on the survey of existing pixel-based classification algorithms (Lu and Weng 2007) and suggestions on the selection of classifiers (Shafri, Suhaili, and Mansor 2007; Mountrakis, Im, and Ogole 2011; Du et al. 2012), the method of maximum likelihood was used due to the higher results of the kappa index compared to other classifiers applied to the same LULC classification test.

The maximum likelihood classifier works with the assumption that the distribution of a class sample is normal and calculates the probability that a given pixel belongs to a specific class. Unless a probability threshold is selected, all pixels are classified. Each pixel is assigned to the class that has the highest probability (Shafri, Suhaili, and Mansor 2007). The classifier was performed with a set of training data containing the LULC classes. Each TM image was performed with a respective set of training data. The classification results for each scene of the same year were mosaicked, generating the LULC map. For the refinements of the classification procedure (over the LULC maps), a majority filter was applied with a window size of  $3 \times 3$  pixels to reassign an LULC class to the center of the  $3 \times 3$  window.

For the supervised classification we used a stratified random sample of 90 percent from the training data. For the accuracy assessment we used the 10 percent of remaining training data–validation samples. The set of validation samples and the LULC maps generated results for global accuracy, omission, and commission errors. These parameters were calculated from the confusion matrix (Pontius and Millones 2011).

#### Forest Cover Changes

To determine the gross rate of forest gain and its persistence through time (SS forests), deforestation, and unchanged forest vegetation (the forest cover class mapped in 1985 that persisted in 2011, or stable forest), we applied a postclassification comparison using a geographic information system (GIS). This method compared two independently produced LULC maps from images of two diferent dates (Yang and Lo 2002) through band operations (Equations 1–3). All classes were converted to the value 0 (nonforest), except the forest cover class, which was converted to the value 5 (1985), to the value 10 (1995), to the value 20 (2005), and to the value 40 (2011).

$$B_{1985} + B_{1995} = BC_{1995} \tag{1}$$

$$BC_{1995} + B_{2005} = BC_{2005} \tag{2}$$

$$BC_{2005} + B_{2011} = BC_{2011},\tag{3}$$

where *B* is the converted raster map to forest and nonforest; *BC* is the forest cover class represented by the stable forest, and changes deforestation and forest gain. From the BC maps, the annual rate of deforestation (Baumann et al. 2012) was calculated as follows (Equation 4):

$$D = (DA_Y/FC_Y) * 100/a \tag{4}$$

with DA as the deforested area (km<sup>2</sup>) during a time span y, FC is the forested area  $(km^2)$  at the beginning of the same time span, and a is the number of years between TM image acquisitions. The results obtained by the BC maps were overlaid with the LULC maps to identify the contributing classes to the deforestation process and forest gains. The postclassification comparison approach is often used for change detection to examine land cover change trajectories, and the accuracy of the change detection result is the multiplied value of overall accuracy from the two compared thematic maps (Coppin et al. 2004). We performed a consistency assessment of the deforestation detection and forest gain by confirming the land cover trajectory for 150 pixels classified as deforestation, 150 pixels classified as forest gain, and 150 pixels classified as stable forest during the time span of 2005 to 2011 using color composites (TM images) for 2005 and the RapidEye images for 2011 based on a method proposed by Bruggeman, Meyfroidt, and Lambin (2015). Then, we calculated the proportion of forest cover gain  $(FG_Y)$ following Baumann et al. (2012) and Kuemmerle et al. (2009) using Equation 5:

$$FG_Y = (R_Y/NF) * 100/a,$$
 (5)

where *R* is the area not being forested at the beginning of the same time span but forested in the time period *y* (km<sup>2</sup>); *NF* is all nonforested area at the beginning of the same time span (km<sup>2</sup>); and *a* is the number of years between TM image acquisitions. Also, we calculated the relative forest cover net change for the entire period (*RNC*) as suggested by Kuemmerle et al. (2009), as shown in Equation 6:

$$RNC = (FC_{2011}/FC_{1985} - 1) * 100, \qquad (6)$$

where FC is the forest cover (km<sup>2</sup>) of the described time span.

#### Results

#### Land Use and Land Cover

The multitemporal land use and land cover mapping for the Paraíba Valley provided high-accuracy results (confusion matrices, see Appendices A–D) using the maximum likelihood supervised classifier: global accuracy of 85 percent for 1985 and 1995, 88 percent for 2005, and 86 percent for 2011. Figure 2 shows the occupied area in the Paraíba Valley region for each LULC class in the time series.

Widespread land changes were observed during the study period. Between 1985 and 2011, the relative forest cover net change was +74 percent (from 2,696 km<sup>2</sup> to 4,704 km<sup>2</sup>). Eucalyptus increased from 375 km<sup>2</sup> to 863 km<sup>2</sup>, and managed pasture maintained its cover area of 4,033 km<sup>2</sup> between 1985 and 2011. The major change in the Paraíba Valley was the decrease of degraded pasture from 5,692 km<sup>2</sup> in 1985 to 3,400 km<sup>2</sup> in 2011 (–2,291 km<sup>2</sup>).

The hypothesis test was used to assess the compatibility between the training data for the entire time series assuming the reflectance values contained in the training data for 2011 as reference data. For the hypothesis tests with a significance level of 1 percent, all classes, except the bare soil, had the null hypothesis (H<sub>0</sub>:  $\mu = \theta$ ) not rejected, for a total of forty-eight tests (six hypothesis tests for each class in the TM bands 1, 2, 3, 4, 5, and 7; see Table 3). By the hypothesis test, the sets of training data showed coherent levels of reflectance in the time series, providing a confidence level of 99 percent that each pixel of the training data belongs to the assigned LULC class. For thematic mapping approaches based on supervised classification algorithms (e.g., maximum likelihood classifier), the results from the hypothesis tests demonstrate the high confidence level of each sample to represent its respective LULC class.

#### Forest Cover Changes and Land Use Dynamics

Forest cover changes were detected from the 1985, 1995, 2005, and 2011 LULC maps. The overall accuracy for the maps of change reached 72 percent, 74 percent, and 75 percent for 1985 to 1995, 1995 to 2005, and 2005 to 2011, respectively. The consistency assessment of the postclassification between 2005 and 2011 showed that 85 percent of pixels classified as deforested did undergo a change from a forest to a nonforest class, and 89 percent of the pixels classified as forest gain changed from nonforest to forest class. Moreover, 98 percent of the pixels classified as stable forest by the postclassification procedure were forested for the two dates. The annual rate of forest cover gain was 0.92 percent between 1985 and 1995, 0.38 percent between 1995 and 2005, and 0.81 percent between 2005 and 2011.

New forest areas resulting from SS were developed mostly over classes of degraded pasture and managed pasture in the proportions of 74 percent



**Figure 2** (A) Occupied area (km<sup>2</sup>) of land use and land cover classes in the time series. (B) Area changed (km<sup>2</sup>) represents the amount of net loss or net gain for each land use and land cover class across the time series. (Color figure available online.)

and 11 percent, respectively. The stable forest from 1985 remained 88 percent stable during the period of study. The annual rate of deforestation reached 1.9 percent between 1985 and 1995, 1.7 percent between 1995 and 2005, and 2.1 percent between 2005 and 2011. The deforestation shows a decreasing trend for the more advanced stages of SS and for the stable forest as seen in Figure 3. Advanced stages of SS are the areas of stable forest gain throughout the next time spans—SS from  $BC_{1995}$  and SS from  $BC_{2005}$  in Figure 3.

Annual deforestation rates for the stable forest decreased to 0.26 percent between 2005 and 2011 compared to 0.36 percent between 1995 and 2005 and 1.9 percent between 1985 and 1995. At the same time, a trend in deforestation in secondary successional areas was observed. The annual deforestation rate on SS from  $BC_{1995}$  was 1.38 percent between 1995 and 2005; between 2005 and 2011 the annual deforestation rate on SS from  $BC_{2005}$  was 1.21 percent and 0.66 percent on SS from  $BC_{1995}$ . Figure 4 shows the contribution of each LULC class to the deforestation and gross rate of forest gain processes—drivers of forest cover dynamics.

The change analysis allowed us to identify the pressure of eucalyptus plantations on deforestation rates during the period of analysis. After the first period from 1985 to 1995, the deforestation caused by the expansion of this activity occurred mostly over SS areas. These results show that there is a decreasing trend in the pressure of eucalyptus plantations over forest remnants in the Paraíba Valley, yet it remains relevant to areas in SS where higher deforestation rates were observed.

Table 3	Results for the hypothesis	tests applied in	Band 4 for all classes
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Band 4	Sum	Average	SD	ME	UL	LL	2011	Result
Agriculture	1.4141	0.4713	0.0838	0.1248	0.5962	0.3464	0.4046	$H_0: \mu = \theta$
Water	0.1052	0.0351	0.0084	0.01260	0.0476	0.0224	0.0265	$H_0: \mu = \theta$
Built-up	0.8604	0.2868	0.0475	0.0708	0.3576	0.2159	0.2574	$H_0: \mu = \theta$
Eucalyptus	1.5431	0.5143	0.1958	0.2917	0.8061	0.2225	0.4099	$H_0: \mu = \theta$
Forest	0.9499	0.3166	0.0428	0.0638	0.3804	0.2528	0.2745	$H_0: \mu = \theta$
Managed pasture	1.1313	0.3771	0.0752	0.1120	0.4891	0.2650	0.2973	$H_0: \mu = \theta$
Degraded pasture	0.9611	0.3203	0.0579	0.0863	0.4066	0.2339	0.2653	$H_0: \mu = \theta$
Bare soil	0.8061	0.2687	0.0541	0.0805	0.3492	0.1881	0.1679	$H_1: \mu \neq \theta$

Note: The same test was applied to Bands 2, 3, 5, and 7 of the TM/Landsat-5. Sum = addition of the mean reflectance values for 1985, 1995, and 2005; Average = average value for 1985, 1995, and 2005; ME = margin of error; UL = upper limit of the two-tailed hypothesis test; LL = lower limit of the two-tailed hypothesis test. The value of confidence interval (Z) at 1 percent was 2.53.



**Figure 3** Stable forest and secondary succession dynamics between 1985 and 2011 in the Paraíba Valley. The gross rate of forest gain is the initial stage of secondary succession. The percentage values are relative to the area of the study region (14,500 km<sup>2</sup>). (Color figure available online.)

# Discussion

# Mapping Techniques

This article explored the spectral relationship between LULC classes in a Landsat-5 TM time series for the purposes of multitemporal classifications. The LULC maps and the postclassification comparison with GIS allowed the analysis of forest cover process changes

through the time series. Taking into account the challenges behind LULC classifications for specific dates where there is little if any ancillary information, the procedures explored to develop the training data for dates prior to 2011 (reference data) contributed to these advances of multitemporal LULC classification. This statement is possible because the results from the spectral analysis show that the LULC classes are consistent with expected spectral behavior, expressed through constant reflectance values in the time series,



**Figure 4** Each time span presents the contributions per land use class for the processes of gross rate of forest gain and deforestation, Paraíba Valley study region.

and were statistically significant at the 1 percent significance level.

The postclassification comparison provided a dynamic view of forest cover in the transitional landscape of the Paraíba Valley, providing information about the forest stability and the rates of deforestation and forest gain. To monitor land cover changes, Afify (2011) demonstrated the postclassification approach based on two thematic maps generated by the maximum likelihood algorithm as more accurate than principal component analysis, image rationing, and image differencing. Several regions have shown the expansion and recovery of forest cover (e.g., forest transition) over areas where there was land abandonment, a land trajectory related to social, economic, and political changes (Lambin and Meyfroidt 2010; Farinaci and Batistella 2012; Prishchepov et al. 2012). The results from the Paraíba Valley land cover dynamics reveal that 74 percent of the new forest areas between 1985 and 2011 occurred over areas of degraded pasture and indicate that land abandonment and consequent forest regeneration is a phenomenon observed in this study region and the main trajectory of change should be considered to explain the forest transition process.

#### Regional Atlantic Forest Transition

The forest cover area increased from 2,696 km<sup>2</sup> in 1985 to 4,704 km<sup>2</sup> in 2011, reaching 32 percent of the Paraíba Valley's area. The observed phenomenon reveals a particular regional forest dynamic still not observed within the Atlantic Forest biome (Ferreira, Alves, and Shimabukuro 2014; Fundação SOS Mata Atlântica/ INPE 2014). Over the past fifty years, the Paraíba Valley has undergone a major socioeconomic transition, from being primarily characterized by agricultural production to an industrialized economy, with important contributions to the GDP of São Paulo State (Boffi, Ricci, and Oliveira 2006; Itani et al. 2011). The rural population, which in 1950 was 55 percent of the total population, decreased to 5.3 percent by 2010 (IBGE 2010), and the outmigration process was driven to industrialized municipalities in the region (Vieira 2012). Even as Brazil became a major player in international food commodity markets in recent decades by the development of large-scale production areas (e.g., central and western São Paulo state-sugarcane; Mato Grosso, Mato Grosso do Sul, and Pará states-soybean and beef; western São Paulo and Mato Grosso stateseucalyptus plantations), in the Paraíba Valley the agricultural area for temporary crops (e.g., soybean, corn, sugar cane) decreased 61 percent, from 587.40 km<sup>2</sup> to 225.96 km<sup>2</sup> between 1990 and 2013. In the same period, Brazil's agricultural area increased 44 percent from 459,807.38 km<sup>2</sup> to 664,060.24 km<sup>2</sup> (IBGE-Municipal Agricultural Production<sup>1</sup>). The decline of agricultural activities has significantly influenced land abandonment processes in less suitable areas for agriculture. In the Paraíba Valley, forest regeneration was a consequence of this change.

The Paraíba Valley pasturelands, around 67 percent of the total land area in 1985, decreased to 51 percent by 2011. The number of cattle in the Paraíba Valley increased from 434,053 in 1985 to 669,667 (animal unit) in 2011 (IBGE-Municipal Cattle Survey<sup>2</sup>), indicating that the stocking rate increased from 0.4 to 0.9 AU/ha (animal unit/hectare). Considering only the managed pasture class (Figure 2), the stocking rate changed from 1.07 to 1.66 AU/ha. For the next few years if this trend does not change, the results could be overgrazing with consequent decay in productivity and degradation of pasturelands, or agricultural intensification, both with potential effects on forest and land changes. For the first case, overgrazing will lead the Atlantic forest in Paraíba Valley to new cycles of deforestation or pressure over the successional vegetation, affecting the trend for forest transition. In the second case, the intensification has the potential to promote changes, raising the productivity of the pasturelands and reducing the needs of new lands for cattle, thus contributing to the return of forest covered areas. According to Grau and Aide (2008), the potential switch from production in traditional extensive grazing areas to intensive modern beef production provides opportunities to significantly increase food production while sparing land for nature conservation.

Eucalyptus plantations had a significant role as proximate causes of the Atlantic forest dynamics as a deforestation agent during its period of expansion (from 1985 to 2005) and afterward by releasing pressure over mature forest remnants. The region's eucalyptus plantations are committed to pulp production for trade in the international market. This economic dimension is acting, in the last decade, as a globalization pathway (Lambin and Meyfroidt 2010) to the forest transition (underlying cause) in the Paraíba Valley (Silva 2015). The forestry and pulp companies must follow strict international rules, such as those of the Forest Stewardship Council (FSC) protocol, stimulating the adoption of Brazilian environmental policies and controlling fire events, with a positive impact on the forest transition process (Farinaci 2012; Farinaci, Ferreira, and Batistella 2013).

Based on the Brazilian National System of Conservation Units (Law No. 9985 of 2000), the annual rate of relative forest cover net change within protected areas in the Paraíba Valley observed between 1985 and 2011 was 4.8 percent and 1.53 percent outside the protected areas.

Previous research in the Atlantic forest biome had identified a progressive predominance of secondary forests compared to mature forests, thereby calling attention to a decrease in the capacity of this biome to provide a home to the most sensitive species (Teixeira et al. 2009). In the Paraíba Valley landscapes, 14.72 percent of forest cover area in 2005 was already SS, and 14.07 percent was mature forest (stable forest). The tendency was accentuated in 2011, when 18.57 percent of the forest cover area was SS and 13.61 percent was mature forest. Despite the fact that secondary forests might not ensure home to the most sensitive species, Lira et al. (2012) highlighted the increase of secondary forest areas as important for biodiversity conservation in the biome due to the potential effect of young secondary forests in reducing the isolation of forest remnants and maintaining significant amounts of original biodiversity.

According to the Fundação SOS Mata Atlântica/ INPE (2014), the Atlantic forest biome has presented a stable forest cover area during the last twenty-eight years (1985-2013). The deforestation rates of the forest patches with less anthropic pressure (forest patches with best conditions to support the original biodiversity) decreased from 5,364.8 km<sup>2</sup> to 239.4 km<sup>2</sup> during the same period. Thus, the biome is approaching the point of inflection of the forest transition curve (Rudel et al. 2005). The biome might not necessarily go through the forest transition process, however, as in the case of Thailand, where the decrease of deforestation rates over the last decades was not followed by an increment of new forested areas (Southworth, Nagendra, and Cassidy 2012). National-scale forest surveys might conceal regional forest trajectories (Tucker and Southworth 2005), but our regionally scaled analysis permits a more refined conclusion. This scale relation is pertinent to the case of Paraíba Valley where the forest cover trajectory in the last decades has shown a clear regional forest transition process that is worthy of attention. This mesoscale study might also contribute to the understanding of global and continental scale processes, such as climate change, land use transitions, and ecosystem services. The Paraíba Valley case arises as a strong message to the global community about the potential of environmental regeneration in endangered tropical biomes, such as the Atlantic forest, which has been depleted for centuries.

# Conclusions

The main objective of this research was to quantify LULC and forest cover dynamics over the last decades to investigate the phenomenon of regional forest transition in the Atlantic forest of Brazil's Paraiba Valley. As the results demonstrate, the research presented the first case of regional forest transition in the Atlantic forest biome in São Paulo State, highlighting the potential of forest regrowth over deforested lands. These results should stimulate studies to assess the effects on biodiversity and ecosystem functions, as well as to inform conservation policies and strategies guiding ecological restoration projects. From the analysis of forest cover dynamics, we concluded that deforestation rates in the Paraíba Valley tended to decrease as well as concentrate on early stages of SS. This result indicates pressure reduction exerted by deforestation over mature forests and on advanced stages of successional forest. The highest contribution of deforestation by eucalyptus plantations was in 2005 to 2011. A total of 86.7 percent of this contribution was concentrated in secondary successional areas, though, indicating a tendency to diminish the pressure exerted by eucalyptus plantations on Atlantic forest remnants. The Paraíba Valley seems to

be undergoing a process of landscape change where the gains of new areas of forest are greater than losses from deforestation; that is, the area is experiencing a forest transition (Rudel, Schneider, and Uriarte 2010). This process is still recent and requires further studies and long-term monitoring to assess its stability. The dynamics of LULC changes illustrate that degraded pasture, considered as land use abandonment, is important to the forest cover gain. This phenomenon indicates that the underlying causes of changes, such as the effect of economic development, the international market rules (pulp from eucalyptus), public policies, massive rural-to-urban migration, and agricultural modernization have played a fundamental role in the land change trajectories and have resulted in a regional Atlantic forest transition in the Paraíba Valley.

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# Notes

- <sup>1</sup> Municipal Agricultural Production: Systematic rural census addressed to rural properties in the Brazilian countryside every year since 1990. See http://www.sidra.ibge.gov.br/ bda/pesquisas/pam/default.asp?o=28&i=P (last accessed 8 July 2015).
- <sup>2</sup> Municipal Cattle Survey: Systematic rural census addressed to rural properties in the Brazilian countryside every year since 1974. See http://www.sidra.ibge.gov.br/bda/pesquisas/ ppm/default.asp?o=27&i=P (last accessed 8 July 2015).

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Appendix A	Estimated population matrix	based on 589 pixels (10	percent of training data),	thematic map of 1985
прреник п	Louinated population matrix	Dasca on 505 pixels (10	percent or training data,	thematic map of 1000

		Reference (%)										
Population (pixel)	Classified	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Total MAP proportion	Commission error	
604824	Class 1	3.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.00	0.00	
270964	Class 2	0.00	2.00	0.00	0.00	0.00	0.00	0.00	0.00	2.00	0.00	
442433	Class 3	0.00	0.00	2.00	0.00	0.00	0.00	0.00	1.00	3.00	1.00	
416774	Class 4	0.00	0.00	0.00	2.00	1.00	0.00	0.00	0.00	3.00	1.00	
2995678	Class 5	1.00	0.00	0.00	0.00	17.0	0.00	0.00	0.00	19.00	1.00	
6325265	Class 6	1.00	0.00	0.00	0.00	1.00	33.00	3.00	1.00	39.00	6.00	
4476719	Class 7	0.00	1.00	0.00	0.00	0.00	4.00	21.00	2.00	28.00	6.00	
586220	Class 8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.00	4.00	0.00	
	Total REF proportion	5.00	2.00	2.00	2.00	19.00	38.00	24.00	7.00	100.00	15.00	
	Omission error	2.00	1.00	0.00	1.00	2.00	4.00	3.00	3.00	15.00		
				Globa	l accuracy	y = 85%						

Note: MAP = thematic map; REF = validation samples; Class 1 = agriculture; Class 2 = water; Class 3 = built-up; Class 4 = eucalyptus; Class 5 = forest; Class 6 = degraded pasture; Class 7 = managed pasture; Class 8 = bare soil.

Appendix B Estimated population matrix based on 600 pixels (10 percent of training data), thematic map of 1995

		Reference (%)										
Population (pixel)	Classified	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Total MAP proportion	Commission error	
232360	Class 1	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.00	0.00	
232082	Class 2	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	2.00	0.00	
510153	Class 3	0.00	0.00	3.00	0.00	0.00	0.00	0.00	1.00	3.00	0.00	
614577	Class 4	0.00	3.00	0.00	3.00	0.00	0.00	0.00	0.00	3.00	1.00	
4207850	Class 5	0.00	1.00	0.00	1.00	24.00	0.00	0.00	0.00	19.00	2.00	
6923142	Class 6	1.00	0.00	0.00	0.00	1.00	33.00	5.00	2.00	39.00	10.00	
3018004	Class 7	0.00	1.00	0.00	0.00	0.00	1.00	17.00	0.00	28.00	2.00	
381246	Class 8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.00	4.00	0.00	
	Total REF proportion	3.00	2.00	3.00	5.00	25.00	35.00	22.00	5.00	100.00	15.00	
	Omission error	1.00	1.00	0.00	2.00	1.00	2.00	5.00	3.00	15.00		
				Globa	accuracy	y = 85%						

Note: MAP = thematic map; REF = validation samples; Class 1 = agriculture; Class 2 = water; Class 3 = built-up; Class 4 = eucalyptus; Class 5 = forest; Class 6 = degraded pasture; Class 7 = managed pasture; Class 8 = bare soil.

Appendix C Estimated population matrix based on 681 pixels (10 percent of training data), thematic map of 2005

		Reference (%)										
Population (pixel)	Classified	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Total MAP proportion	Commission error	
649517	Class 1	3.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	4.00	0.00	
302121	Class 2	0.00	2.00	0.00	0.00	0.00	0.00	0.00	0.00	2.00	0.00	
515981	Class 3	0.00	0.00	3.00	0.00	0.00	0.00	0.00	0.00	3.00	0.00	
544594	Class 4	0.00	0.00	0.00	3.00	0.00	0.00	0.00	0.00	3.00	1.00	
4668882	Class 5	0.00	0.00	0.00	1.00	27.00	1.00	0.00	0.00	29.00	2.00	
5774987	Class 6	0.00	0.00	0.00	0.00	1.00	31.00	3.00	1.00	36.00	10.00	
3385715	Class 7	0.00	0.00	0.00	0.00	0.00	2.00	18.00	1.00	21.00	2.00	
278190	Class 8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2.00	0.00	
	Total REF proportion	3.00	3.00	3.00	5.00	27.00	35.00	22.00	3.00	100.00	12.00	
	Omission error	0.00	1.00	0.00 Globa	1.00 Il accuraci	0.00 y = 88%	3.00	4.00	2.00	12.00		

Note: MAP = thematic map; REF = validation samples; Class 1 = agriculture; Class 2 = water; Class 3 = built-up; Class 4 = eucalyptus; Class 5 = forest; Class 6 = degraded pasture; Class 7 = managed pasture; Class 8 = bare soil.

Annendiv D	Estimated	nonulation	matrix hasoc	l on 807	nivals (10	nercent of	f training data	thematic ma	n of 2011
Appendix D	LSUITIALEU	ιορυιατιοπ	IIIaliix Daseu	011007	pixels (10	percentor	i ti ali ili ig uata)	, แกษกาลแบกกล	p o z o i i

	Reference (%)											
Population (pixel)	Classified	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Total MAP proportion	Commission error	
580519	Class 1	3.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.00	1.00	
301433	Class 2	0.00	2.00	0.00	0.00	0.00	0.00	0.00	0.00	2.00	0.00	
623293	Class 3	0.00	0.00	3.00	0.00	0.00	0.00	0.00	0.00	4.00	0.00	
959938	Class 4	0.00	0.00	0.00	5.00	1.00	0.00	0.00	0.00	6.00	1.00	
5226685	Class 5	0.00	0.00	0.00	2.00	29.00	1.00	0.00	0.00	32.00	3.00	
3778798	Class 6	0.00	0.00	0.00	0.00	0.00	21.00	1.00	1.00	23.00	3.00	
4481386	Class 7	0.00	0.00	0.00	0.00	0.00	4.00	21.00	2.00	28.00	7.00	
169452	Class 8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	
	Total REF proportion	4.00	2.00	4.00	8.00	30.00	26.00	22.00	4.00	100.000	14.00	
	Omission error	1.00	1.00	0.00	3.00	1.00	5.00	1.00	3.00	14.00		
Global acour	201 - 96%											

Global accuracy = 86%

Note: MAP = thematic map; REF = validation samples; Class 1 = agriculture; Class 2 = water; Class 3 = built-up; Class 4 = eucalyptus; Class 5 = forest; Class 6 = degraded pasture; Class 7 = managed pasture; Class 8 = bare soil.